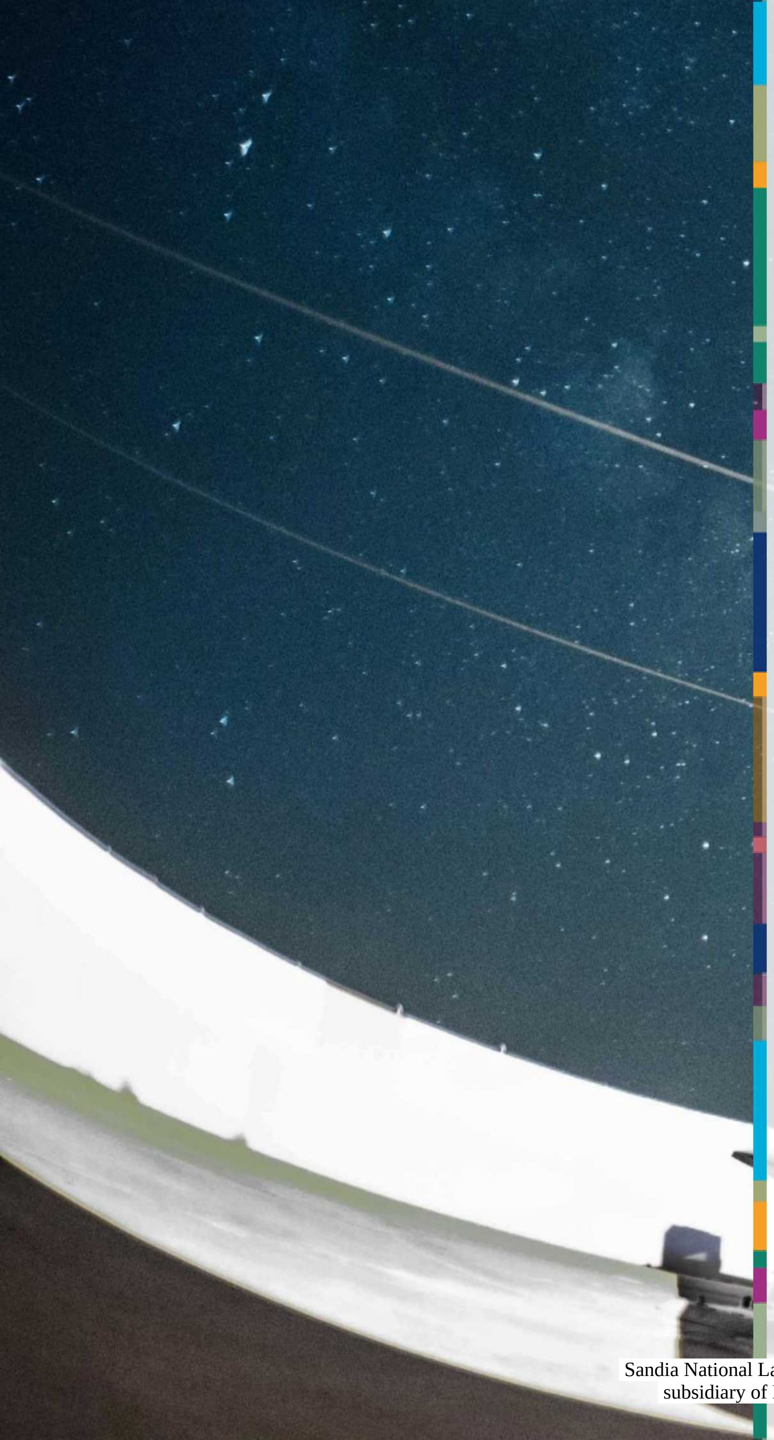

New Mexico Research Spotlight Forum

SAND2019-1136PE

1/29/2019 Artificial Intelligence & Machine Learning

WELCOME & DISCOVERY RESEARCH IN AI

PRESENTED BY:

Gil Herrera

Director, Advanced Science & Technology

Sandia National Laboratories

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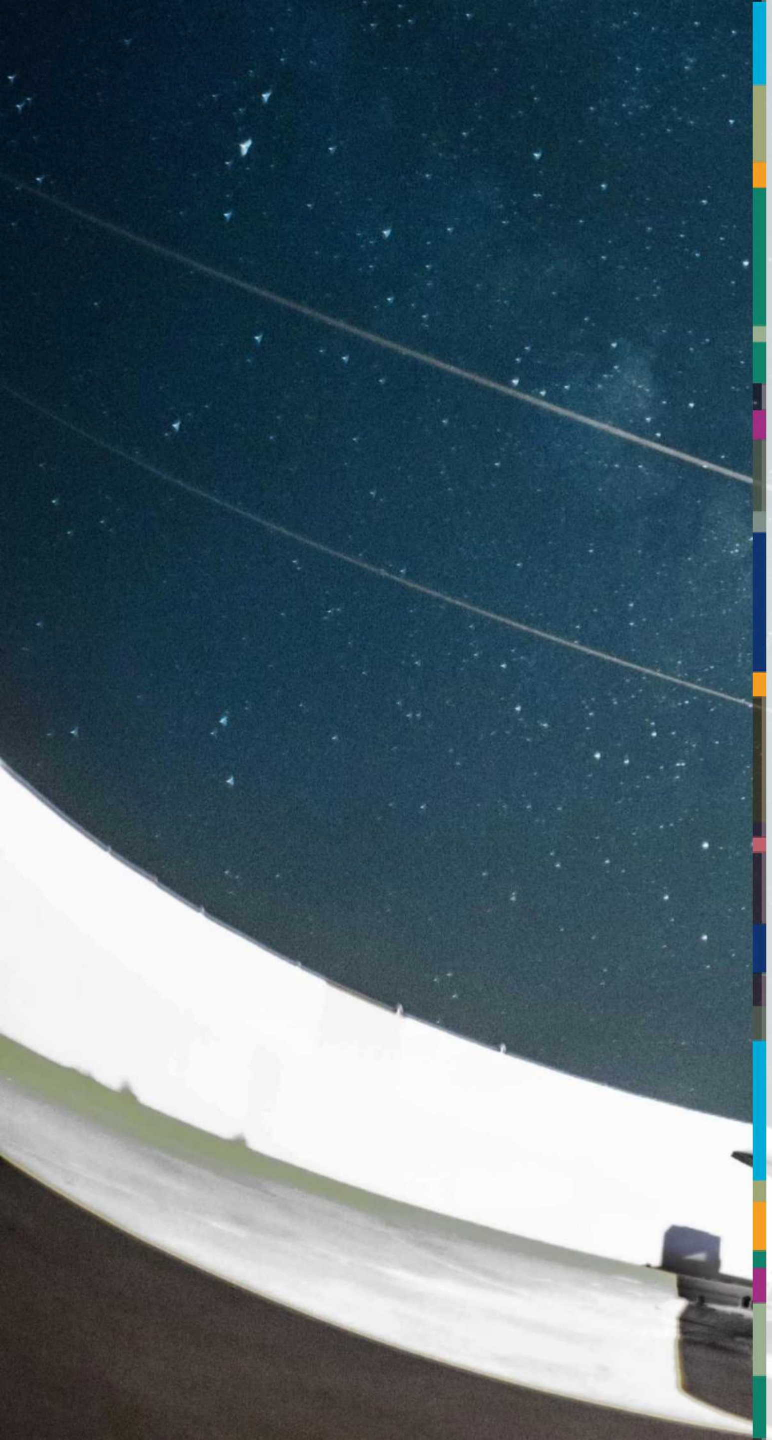

New Mexico Research Spotlight Forum

1/29/2019 Artificial Intelligence & Machine Learning

Machine Learning for National Security

PRESENTED BY:

Tu- Thach Quach, Threat Intelligence Center

Sandia National Laboratories

Program Overview

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SAND2019-0808 PE

Outline

Task-Specific Compressive Imaging

Sparse Memory Acquisition on Neuromorphic Hardware

Vehicle Track Segmentation

Common theme:

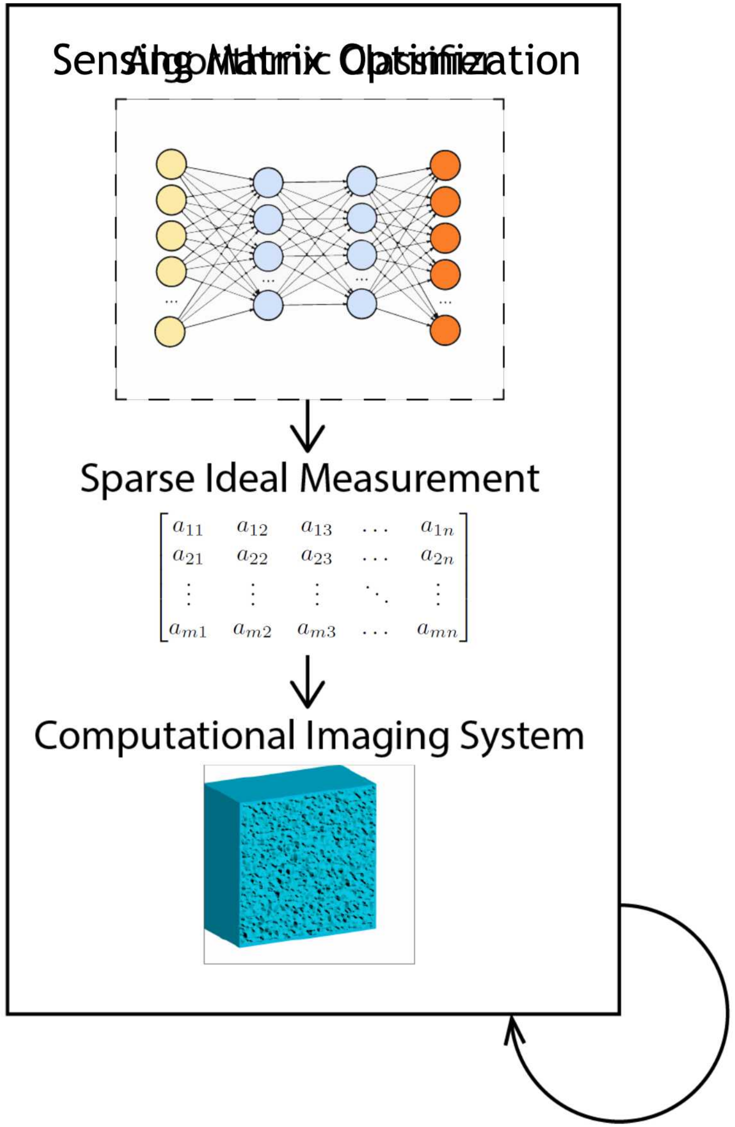
- Size, Weight, and Power (SWaP)
- Data

Task-Specific Compressive Imaging

Merging of both optical hardware and algorithmic elements to create novel imaging architectures that reduce size, weight, and power (SWaP)

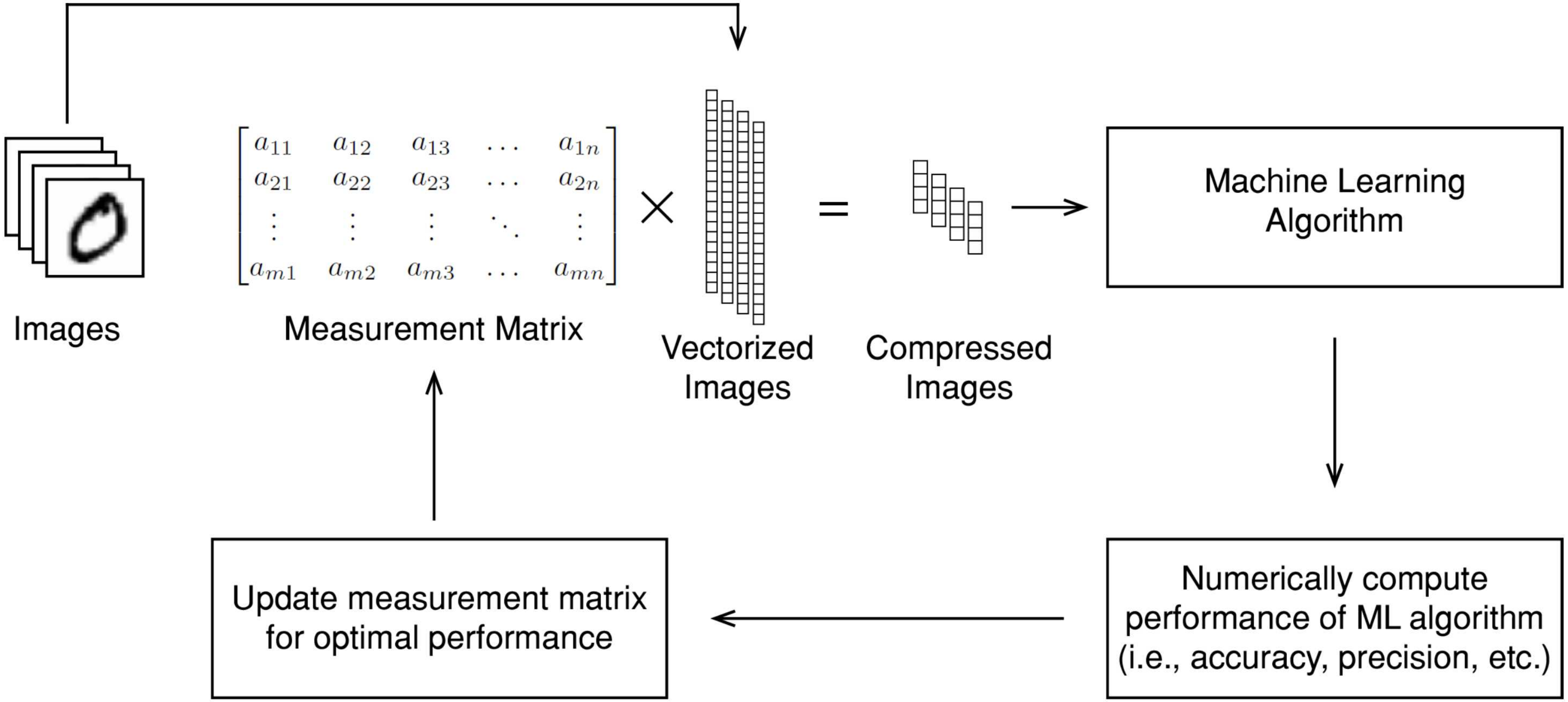
Approach:

1. Finding optimal sensing matrix that still enables classification and reconstruction
2. Design optical hardware informed by optimal sensing matrix

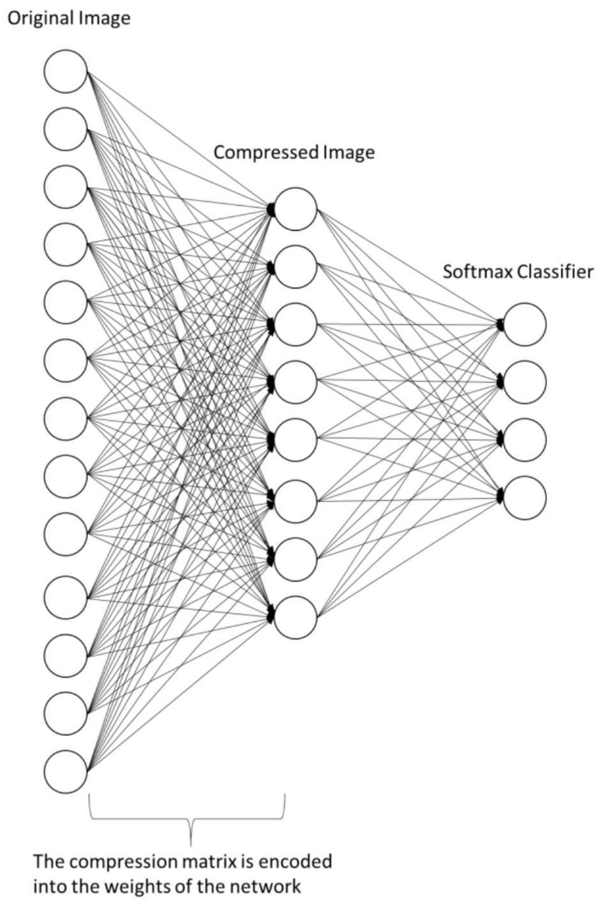


Birch, Quach, Galiardi, LaCasse, Dagel, "Optical systems for task-specific compressive classification," Optics and Photonics for Information Processing XII, 2018

Ideal Measurement Matrix: Conceptual Approach

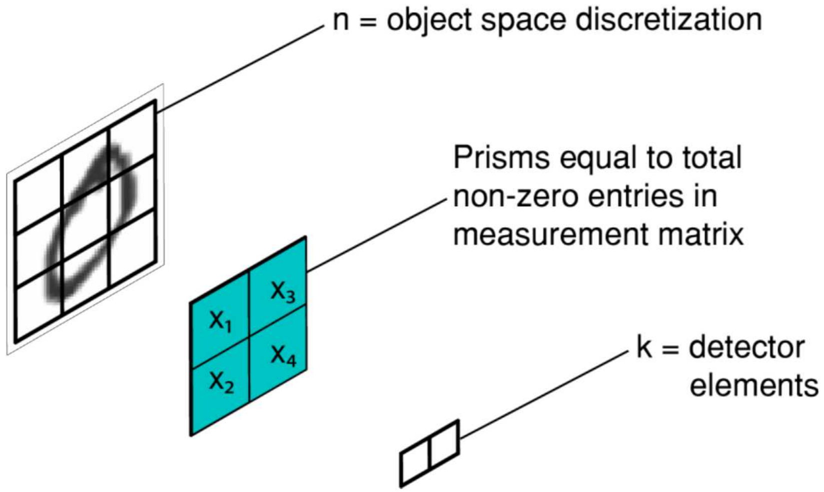


Implementation: Neural Network Approach

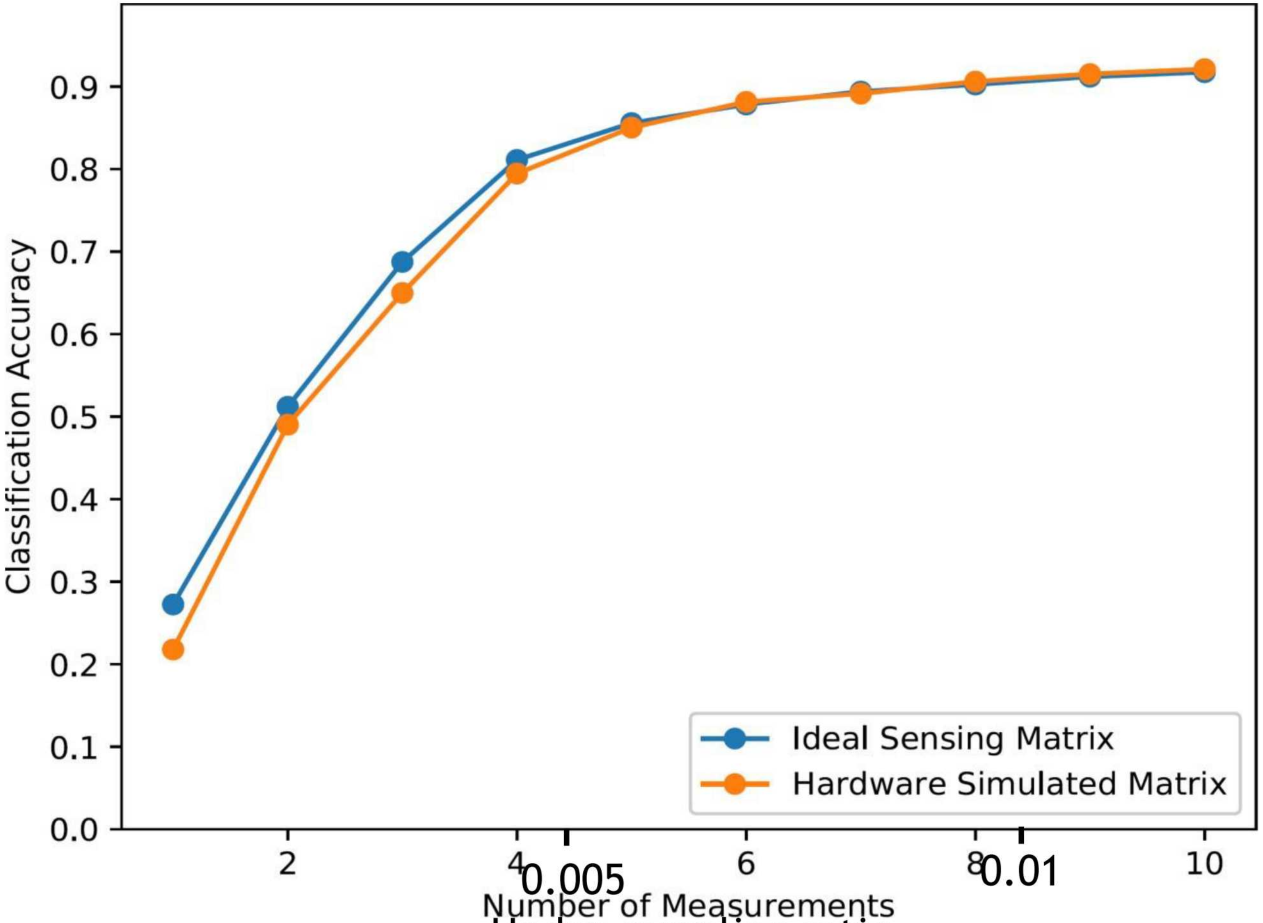


$$\underset{A,\theta}{\text{minimize}} \quad \lambda||A||_1 - \sum_{x \in \mathcal{X}} \sum_{c \in \mathcal{C}} [c = c_x] \log p_\theta(c|Ax)$$
$$\text{s.t.} \quad a_{ij} \geq 0$$

Hardware simulated as prism arrays



Simulation Results: Ideal vs. Simulated Hardware

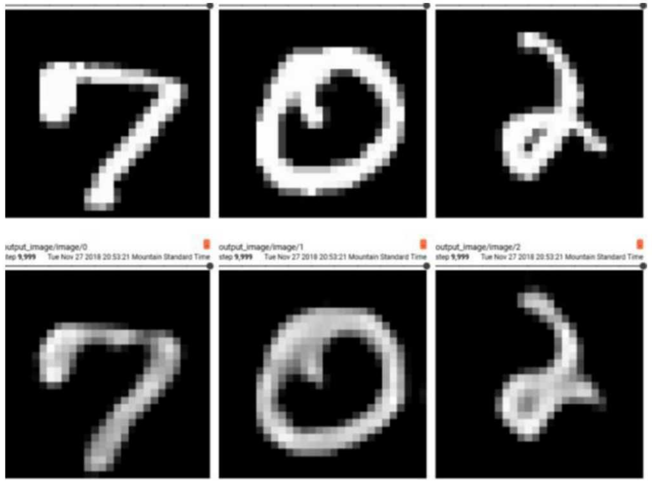


0.005 0.01

Under-sampling ratio

Input

Reconstruction



Input

Reconstruction

PSNR: 10 dB

Summary: Task-Specific Imaging

Task-specific sensing system can be designed and optimized to improve performance and reduce SWaP constraints

Initial refractive prism array hardware simulation shows promising results similar to ideal measurement matrix

Hardware simulations show tolerance for aberrations such as defocus and stray light

- Future work will investigate if aberrations from other optical elements can be accounted for in the design of the custom optical element, or can be mitigated in the classifier
- Relationship between aberration, data compression, and task performance is complex, and may be exploitable

Multiphoton lithography will be investigated as a means to realize task-specific optical elements

Outline

Task-Specific Compressive Imaging

Sparse Memory Acquisition on NeuromorphicHardware

Vehicle Track Segmentation

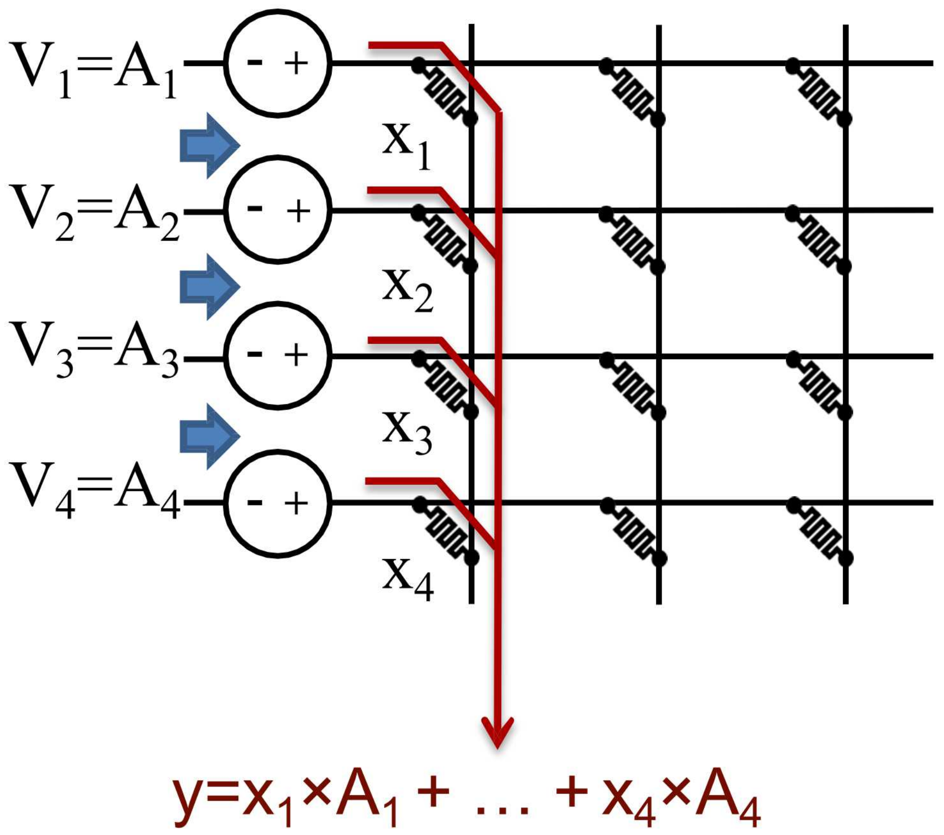
Memory Acquisition

Memory devices, both volatile and non-volatile, have the capacity to store large amounts of data

- Sequentially reading out memory content can be slow

Need fast acquisition time for high-throughput applications, such as memory forensics

Approach: Sparse sampling on neuromorphic memory devices such as resistive memories



Quach, Agarwal, James, Marinella, Aimone, "Sparse Data Acquisition on Emerging Memory Architectures," IEEE Access, 2019

Passive Sampling

$$\begin{bmatrix} a_{11} & a_{12} & a_{13} & \cdots & a_{1n} \\ a_{21} & a_{22} & a_{23} & \cdots & a_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & a_{m3} & \cdots & a_{mn} \end{bmatrix}$$

- d ones per column
  - Satisfies Restricted Isometry Property:

$$(1-\delta)||x||_1 \leq ||Ax||_1 \leq (1+\delta)||x||_1$$

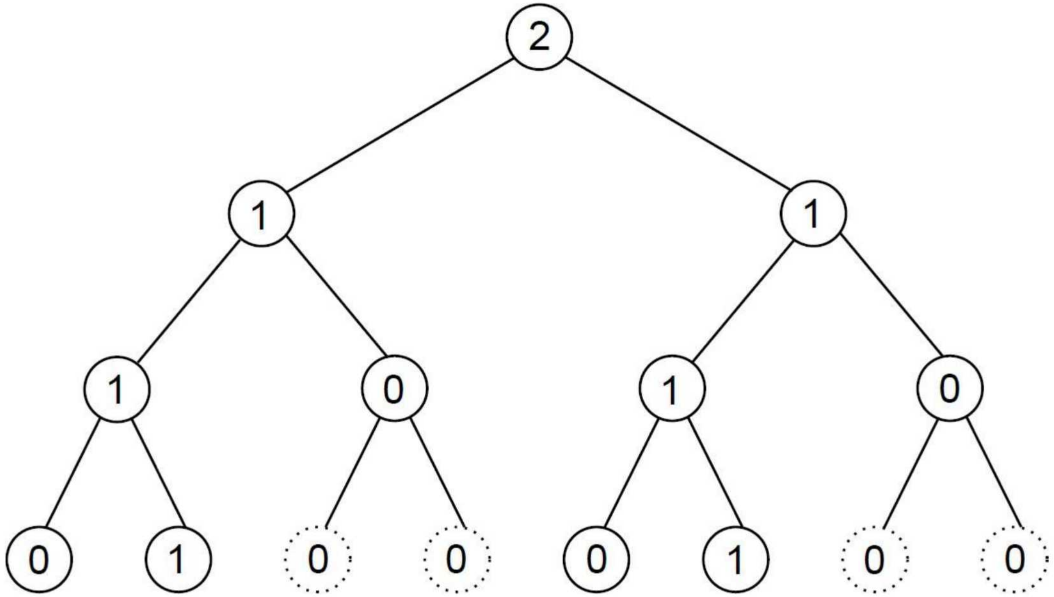
- At most $\lceil nd/m \rceil$ per row
  - Minimize A/D converter saturation

Algorithm 1 Sampling Matrix

```
Input: m, n, d
Output: A
A ← zero m-by-n matrix
o ← zero m-by-1 vector                ▷ # of ones in each row
j ← 1
while j ≤ n do
    o′ ← o
    Q ← empty priority queue
    w ← random m-by-1 vector
    for i ← 1 to m do
        Q.enqueue(i, o_i, w_i)
    for l ← 1 to d do
        i ← Q.dequeue()
        A_ij ← 1
        o_i ← o_i + 1
    if A_·j is unique then
        j ← j + 1
    else
        A_·j ← 0
        o ← o′
```

- Require post reconstruction step: $\min_{\alpha} ||\alpha||_1 \quad \text{subject to} \quad A\alpha = y$

Adaptive Sampling



- Repeatedly sample non-zero partition by splitting into halves until partition value is 0 or equal to partition size

- No post reconstruction step is needed

Algorithm 2 Adaptive Sampling

Input: vector $x = (x_0, \ldots, x_{n-1})$, $x_i \in \{0, 1\}$
Output: $\hat{x}$
$\hat{x} \leftarrow$ zero vector of length n
$Q \leftarrow$ empty queue
Q.enqueue$(0, n)$
while Q is not empty **do**
  $a, b \leftarrow Q$.dequeue()
  $t = \sum_{i=a}^{b-1} x_i$ ▷ sample x
  if $t > 0$ **then**
    if $b - a = 1$ **then** ▷ Leaf node
      $\hat{x}_a \leftarrow t$
    else
      $i \leftarrow (b - a)/2$
      Q.enqueue$(a, a + i)$ ▷ Left node
      Q.enqueue$(a + i, b)$ ▷ Right node

Properties

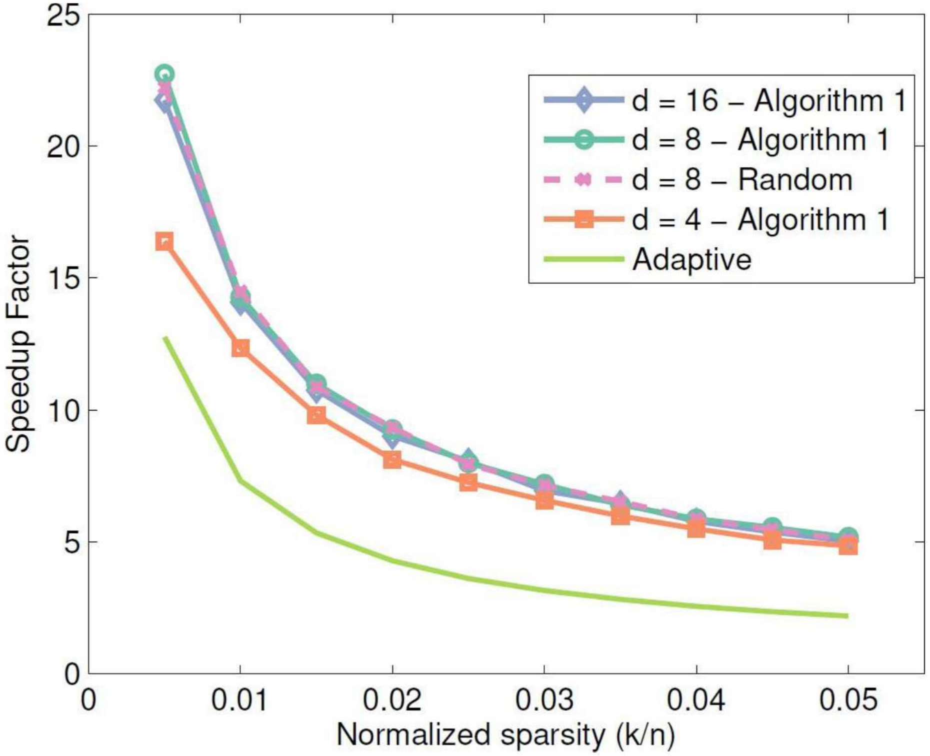
	Sequential	Passive Sampling	Adaptive Sampling
Time	$O(n)$	$\boldsymbol{O(k \log n/k)}$	$\boldsymbol{O(k \log n/k)}$
Energy	$O(n^3 + n^3/c)$	$O(n^3 dc + n^2 k \log n/k)$	$O(n^3 \log k + n^2 k \log n/k)$

n elements in a crossbar column with k ones in the column
c columns can be read in parallel

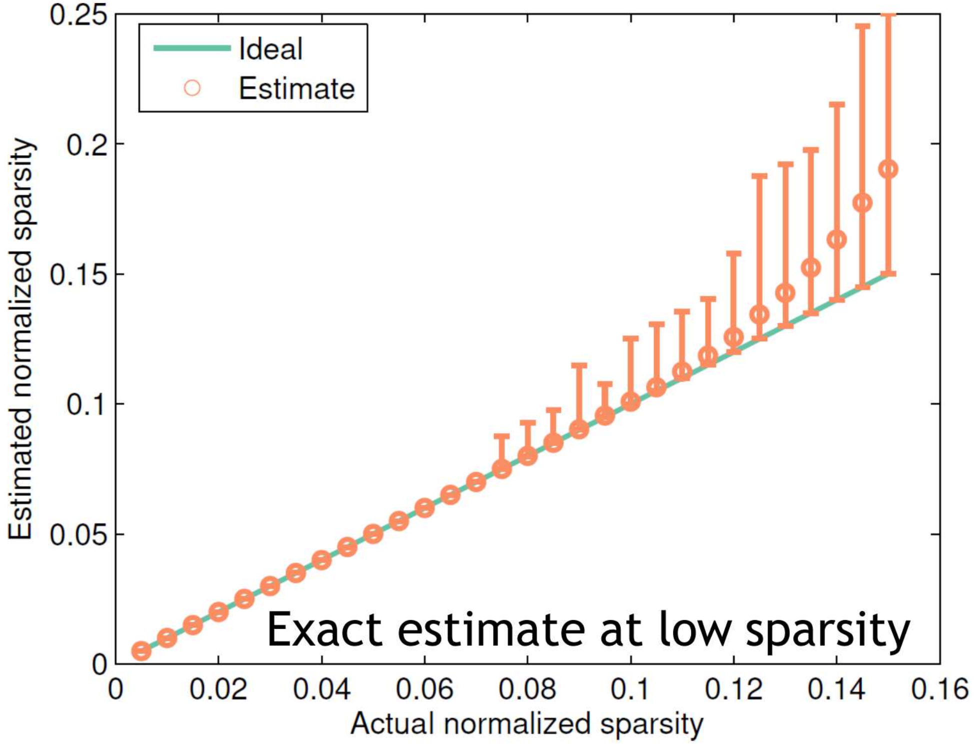
Both passive and adaptive sampling reduces memory acquisition time from linear to sub-linear

Simulation Results with 4-bit A/D Converter

Speedup Factor



Sparsity Estimate



Summary: Memory Acquisition

Resistive memory devices provide convenient summation kernel that enables sparse sampling

Both passive and adaptive sampling reduces sampling time from linear to sub-linear for sparse memory content

Sparse regions of memory can be identified to selectively apply sampling process

Experiments indicate speedup factors of more than 20x

Future work: extend adaptive algorithm to sample multiple crossbar columns

Task-Specific Compressive Imaging

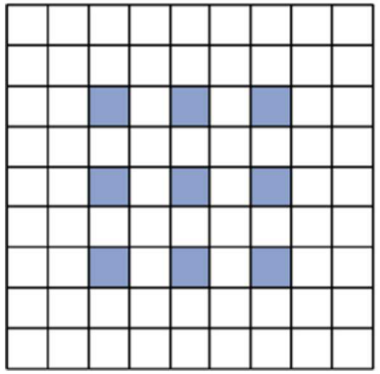
Sparse Memory Acquisition on Neuromorphic Hardware

Vehicle Track Segmentation

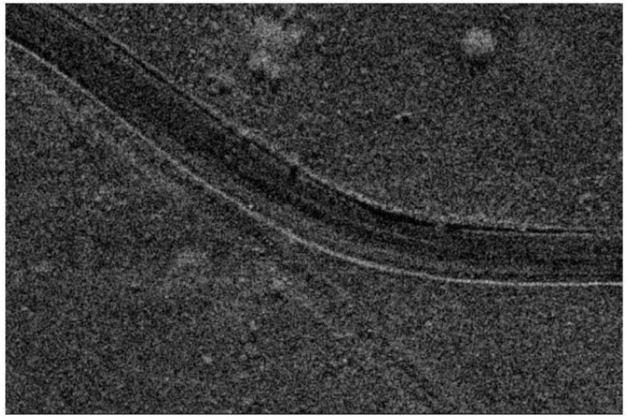
Segment vehicle tracks in synthetic aperture radar (SAR) change coherent detection (CCD) images

Approach:

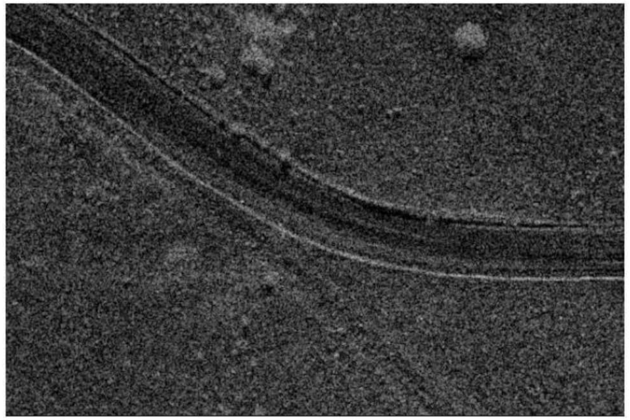
- Random Fields
- Dilated Convolutional Network



Morning SAR



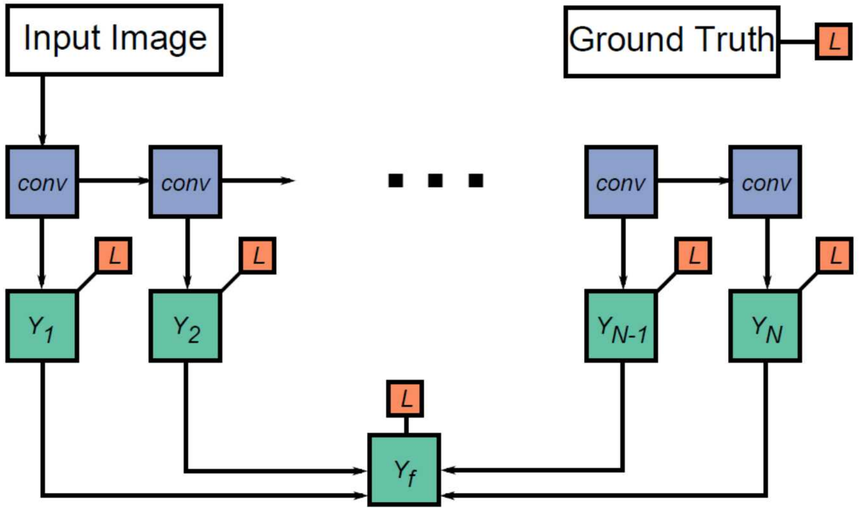
Afternoon SAR



Resulting CCD

Quach, “Vehicle Track Segmentation using Higher Order Random Fields,” IEEE GSRL, 2017
Quach, “Convolutional Networks for Vehicle Track Segmentation,” JARS, 2017

6-Layer Network

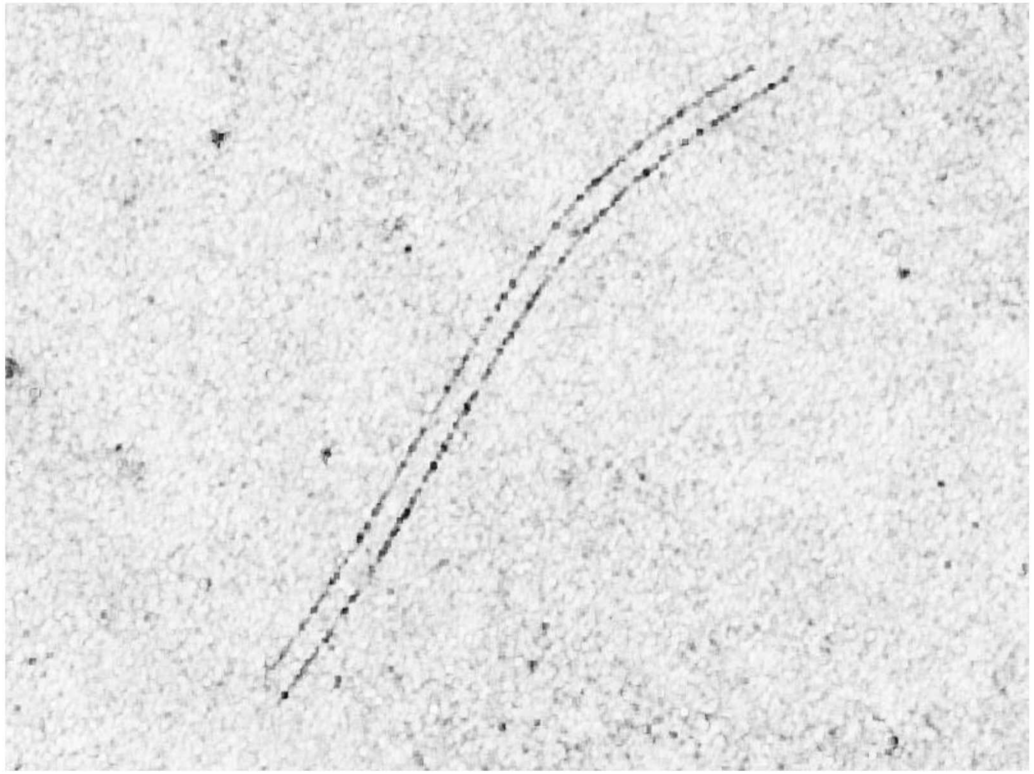


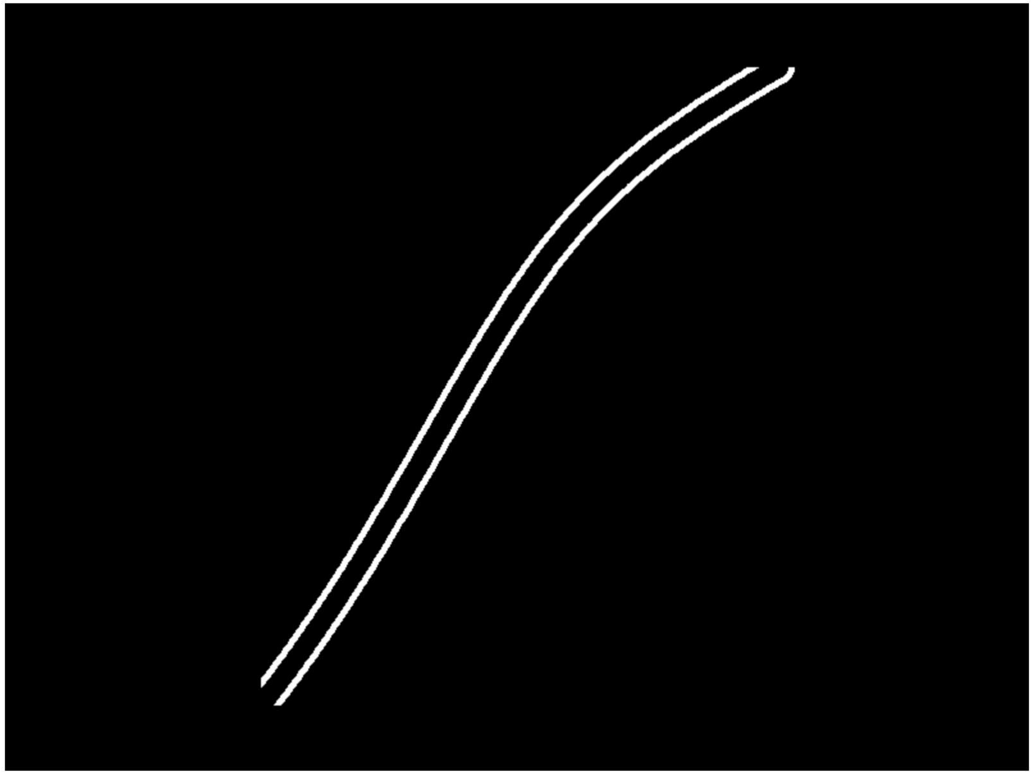
Layer	Dilation Rate	Output Channels	Receptive Field
1	1	32	3
2	2	32	7
3	4	64	15
4	8	64	31
5	16	128	63
6	32	128	127

Dilation network allows for exponential increase in field of view

Training Data

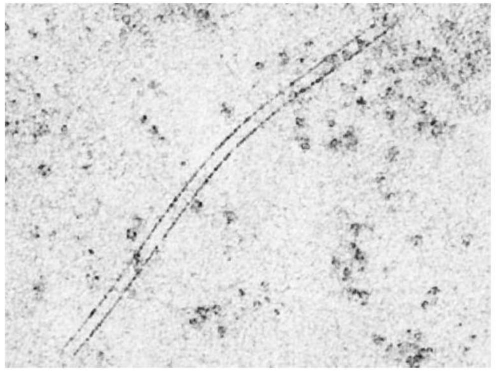
Mostly simulated with some hand-labeled images

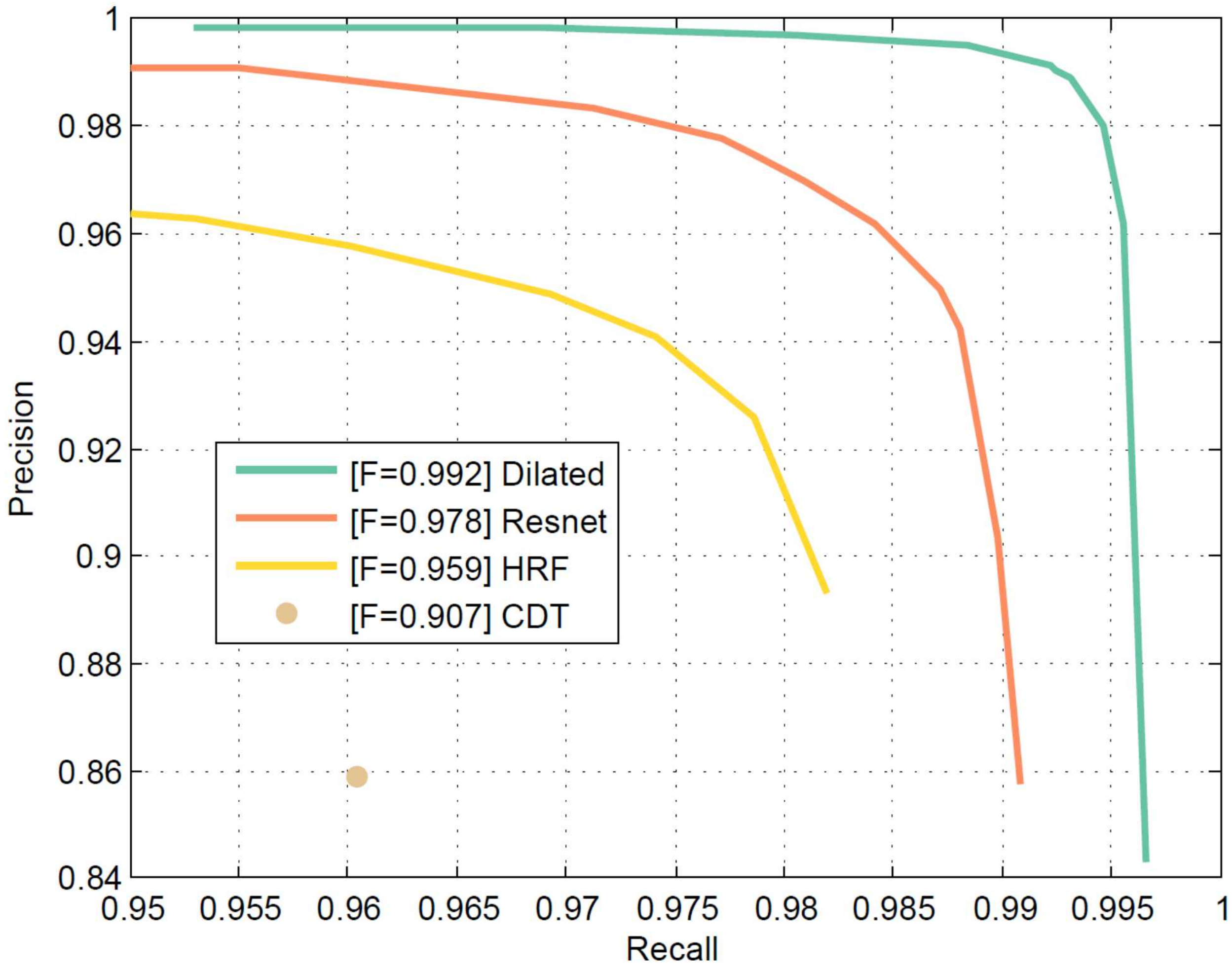


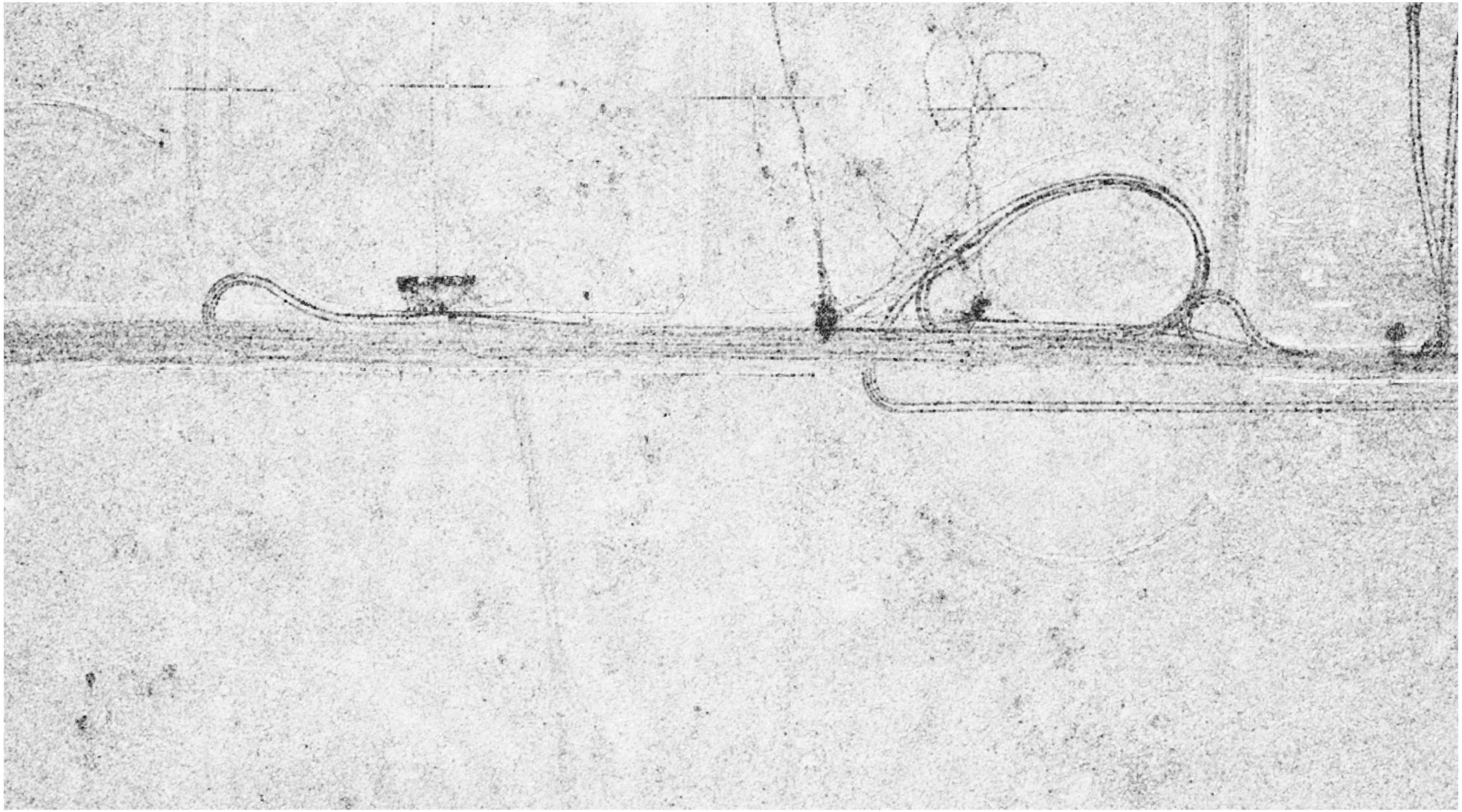


Quantitative Results

Inference time is less than one second on 1000-by-1000 image







Summary: Vehicle Track Segmentation

Small, fast dilated network for vehicle track segmentation

Potential use with commercial tensor-based processors for onboard, SWaP-constrained systems

Simulated training data is promising

Challenges

Absent of training data

- Difficult or time-consuming to create
- Rely on simulations when possible
- Need algorithms that are robust to cross-domain data problems

Size, Weight, and Power (SWaP)

- Need algorithms that can operate in SWaP-constrained environments

Thank You

Tu-Thach Quach

E-mail: tong@sandia.gov

Sandia National Laboratories

Autonomy for Hypersonics

Research Spotlight: Jan. 29, 2019

Alex Roesler, PhD
Deputy Director
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(505) 845-9655

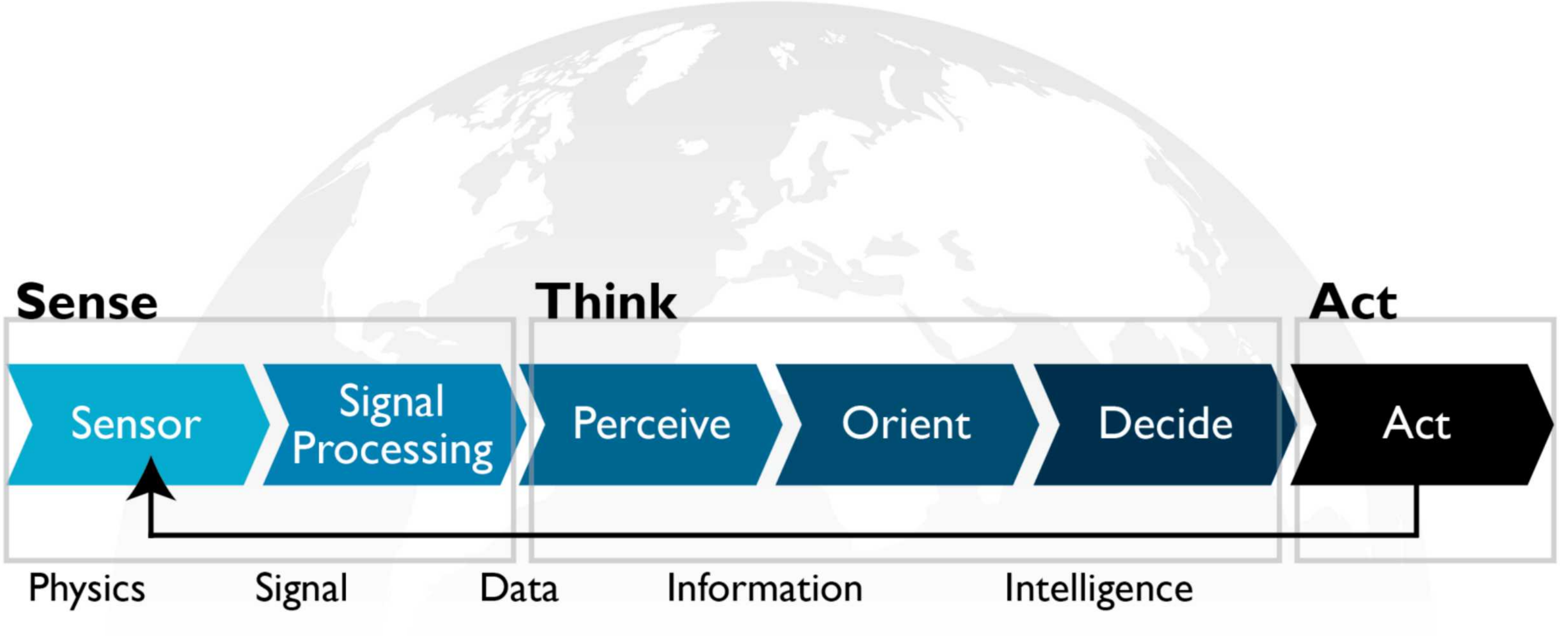
SAND2018-1486 PE

U.S. DEPARTMENT OF ENERGY

National Nuclear Security Administration

Autonomy: What is it?

Autonomous Systems



- Follows Sense-Think-Act paradigm
- Sensors provide signals & data
- Machine intelligence starts with data
- Sensor exploitation (target detection, identification, and characterization) provides information and intelligence
- High-level reasoning and dynamic sensor/platform/asset management close the loop with action

Example: Self-Driving Vehicles


Autonomy for National Security

Will AI tech be plug-n-play for defense?

- Andrew Ng,
Harvard Business Review

The AI community is remarkably open, with most top researchers publishing and sharing ideas and even open-source code. In this world of open source, the scarce resources are therefore:

Data.

Among leading AI teams, many can likely replicate others' software in, at most, 1–2 years. But it is exceedingly difficult to get access to someone else's data. ***Thus data, rather than software, is the defensible barrier for many businesses.***

Talent.

Simply downloading and "applying" open-source software to your data won't work. ***AI needs to be customized to your business context and data.*** This is why there is currently a war for the scarce AI talent that can do this work.

Autonomy for Hypersonics

Hypersonic Weapons

Hypersonics weapons are maneuverable glide vehicles

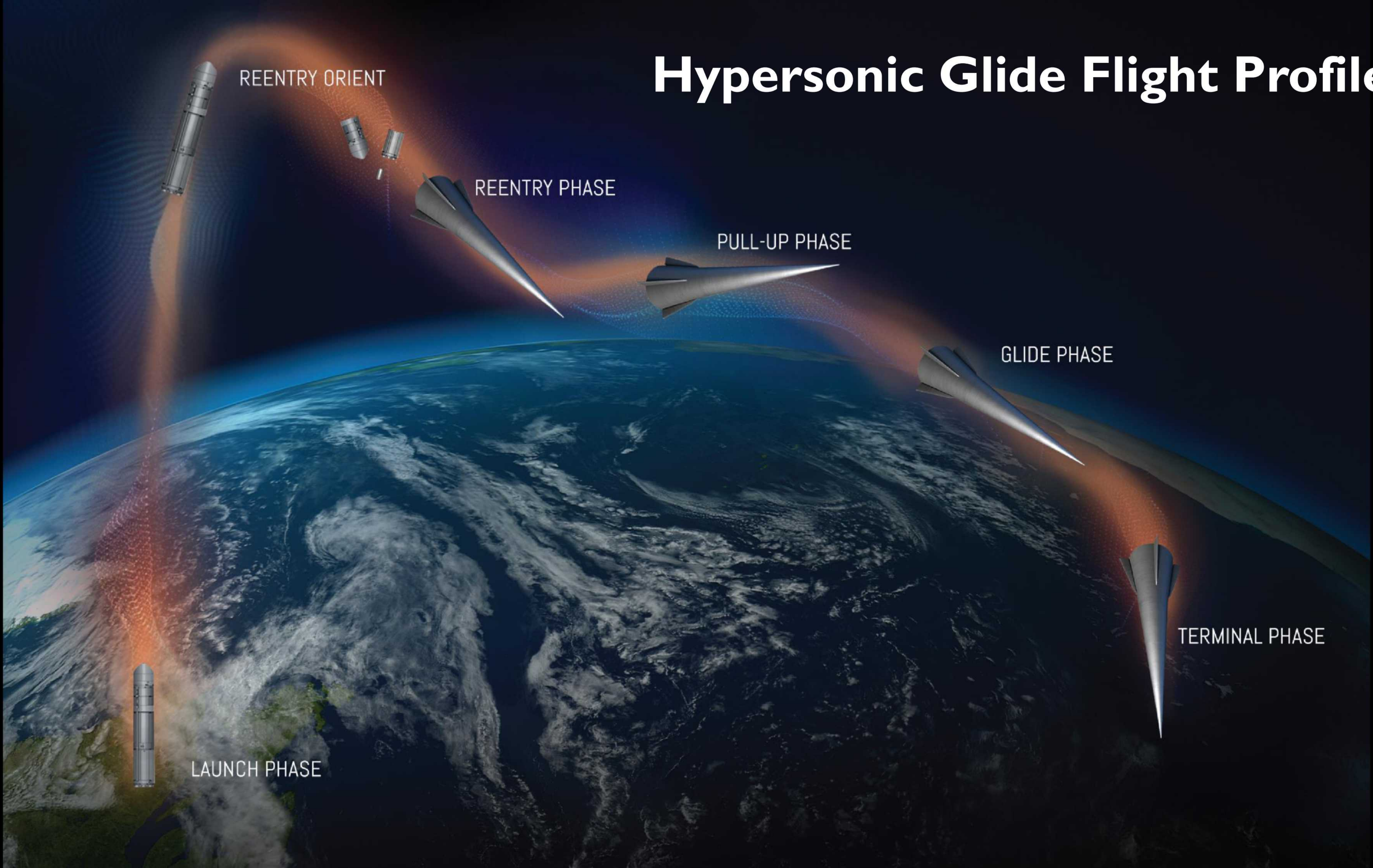
These systems fly at Mach 5 or higher: **approximately one mile per second!**

Engineering Challenges

- Missile shape changes in hypersonic flight, creating challenges for flight control
- Difficult to simulate velocity, temperature, and Mach number on the ground
- Difficult to design sensors & actuators that can operate in a hypersonic flight environment
- Friction and separation happens in ways that cause calculations about material to become 'guesses'
- Calculations are extremely time consuming

Hypersonics fly 3800+ miles per hour

Hypersonic Glide Flight Profile



Autonomy for Hypersonics

A4H will research and develop autonomous systems technologies that will enhance the warfighting utility of hypersonic flight systems

- Provide autonomous mission planning for rapid response to time-sensitive threats
- Enable adaptive, highly-maneuvering vehicles that intelligently navigate, guide, and control themselves and home-in on targets

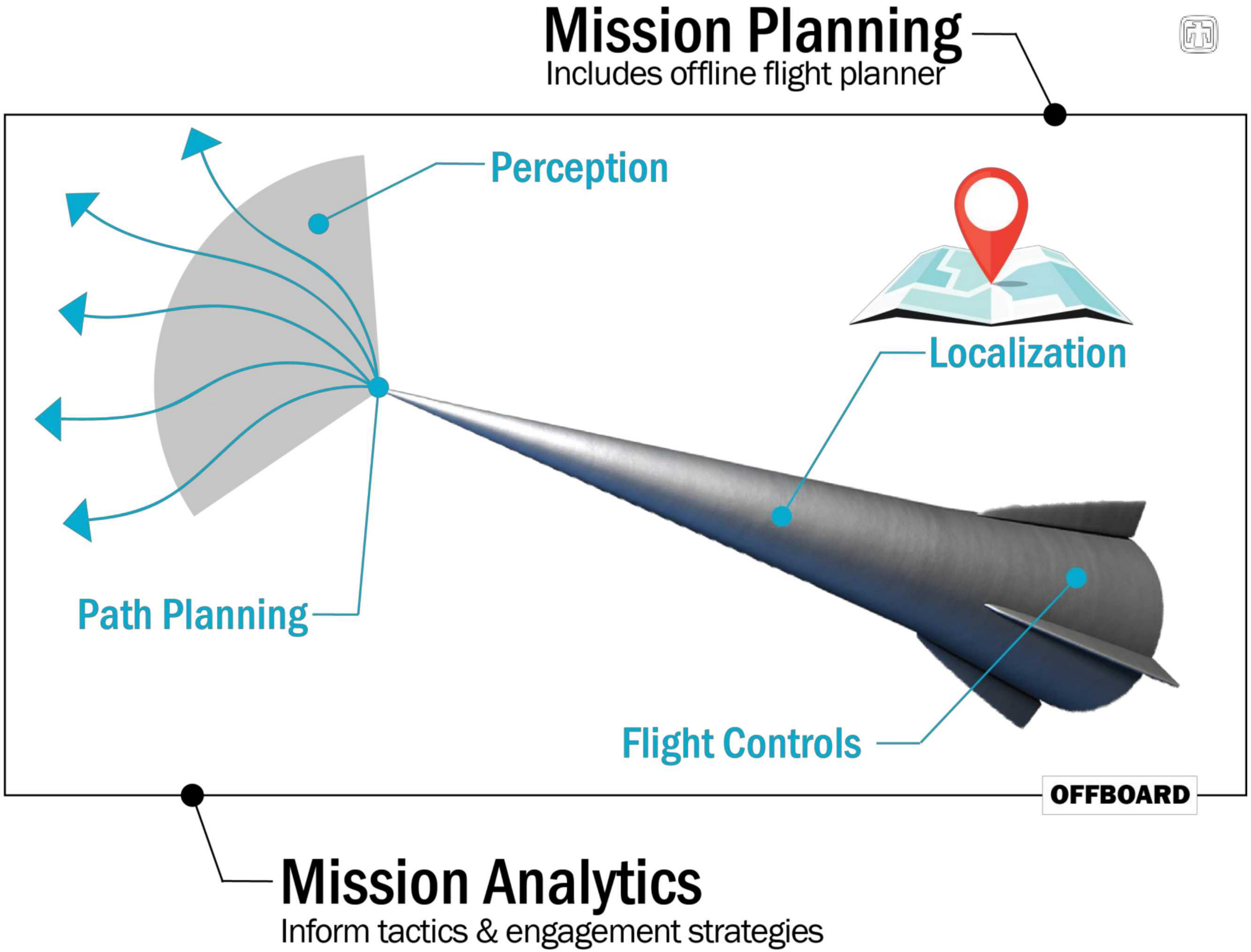
The developed autonomy solutions will strengthen conventional deterrence by enabling adaptive hypersonic systems that can:

- Prosecute fleeting targets in GPS-denied environments
- Provide a defense against adversary hypersonic weapons

Through groundbreaking autonomy research, the A4H Campaign seeks to deliver transformational hypersonic capabilities to help the U.S. regain and retain leadership in this strategically significant area

n

A4H Research Areas



External Partnership Plan: AutonomyNM

Autonomy Innovation Hub for Advanced Flight & Space Systems

Creating a mechanism to "spin-in" ideas that provide transformative autonomy solutions, opportunities for commercialization, and a pipeline of AI and autonomy talent

A4H initiated AutonomyNM, with the goal of promoting and attracting collaborative R&D with Academic Alliance (AA) and university partners

- Helps SNL expand its innovation network in this critical technology area
- Venture track for AA Collaborators: The program will allow SNL and AA researchers to work side-by-side to help university innovators transition their research into end-use applications
- Internship track: AutonomyNM is incorporated under TITANS and provide students an opportunity to research autonomy solutions for advanced flight and space systems
- AutonomyNM Facility: A cutting-edge, modern research environment will promote open communication and innovation, foster creativity, and enable agile creation of startups

New Mexico Research Spotlight Forum

1/29/2019 Artificial Intelligence & Machine Learning

ML & AI Investments in the Computing and Information Science (CIS) Research Foundation

Justin Newcomer, Manager
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Capability Overview

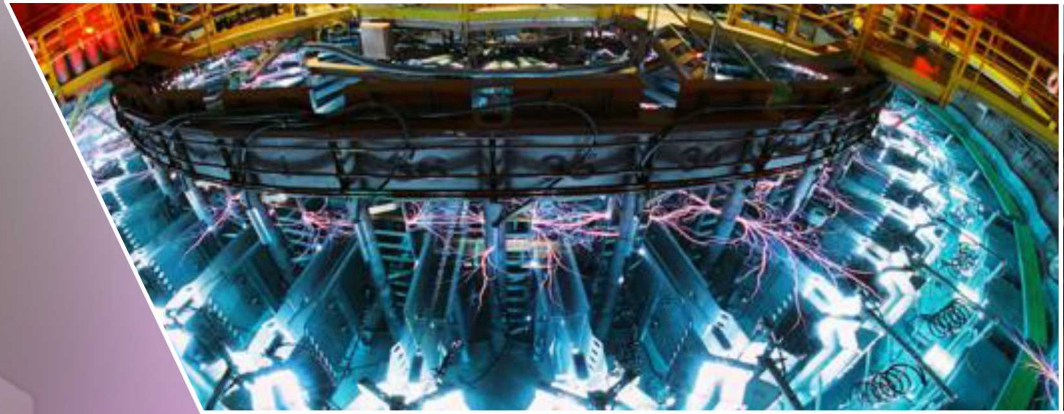
Sandia National Laboratories | The University of New Mexico | NM State University | New Mexico Tech Science • Engineering • Research University

SAND2019-0757 C

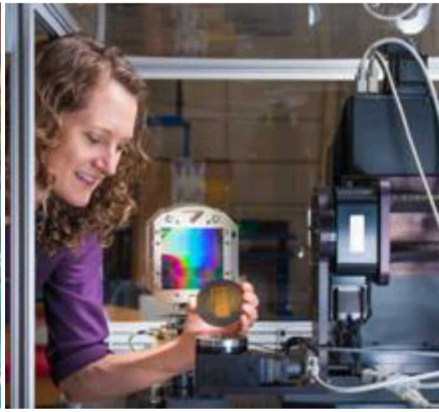
ADVANCED SCIENCE & TECHNOLOGY

Research Foundations play an integral role in mission delivery

Nanodevices & Microsystems

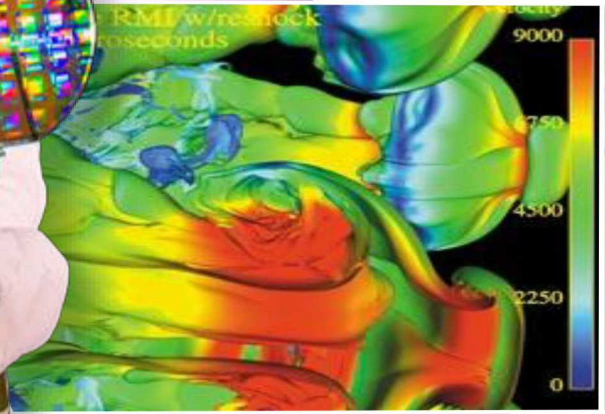


Radiation Effects & High Energy Density Science



Materials Science

Computing & Information Science



Engineering Science

Geoscience

Bioscience

Sandia's Unique Mission Needs

High-confidence decisions

- Typically designing to "Five 9's" of reliability
- Need to assure trust in our solutions
- Need to understand uncertainty of decisions
- Algorithms need to be explainable

Applications consist of large volumes of simulation data but often only small volumes of experimental data

- First principles physics may be known, or not
- Multiple data sources – measured, observed and simulated – with limited, unknown, or no ground truth (no labeling and little to no positives).

Some Sandia national security missions require decisions to be made in a very short time frame (milliseconds to minutes) while other missions have longer time frames (hours to days)

Need to account for potential adversarial issues


Space


Military Systems


Nonproliferation


Weaponeering


Infrastructure Resilience


Homeland Security


Research

Machine Learning (ML) Challenge

Opportunity: Many projects at Sandia are investigating using ML to

- Categorize and discriminate objects and patterns
- Predict outcomes based on machine learned models
- Create reduce order surrogate models
- Automate repetitive computing tasks
- Assist human decision making

Challenges:

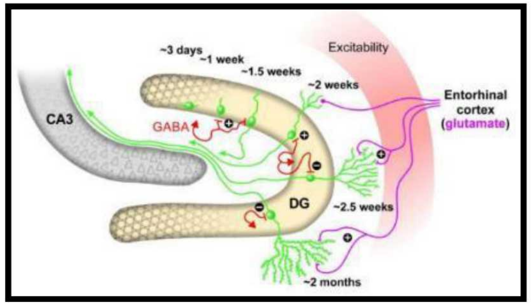
- ML methods are currently being applied to low consequence problems that have substantial training data.
- Overtraining is a common problem that includes noise in the solution.
- Adversarial techniques exist that fool image classifiers.
- Explainability and uncertainty quantification currently don't exist.

Synthesizing Robust Adversarial Examples, Athalye, et.al., 2018

Machine Learning LDRD Research

FY15-FY17 Grand Challenge LDRD in Hardware Acceleration of Adaptive Neural Algorithms (HAANA)

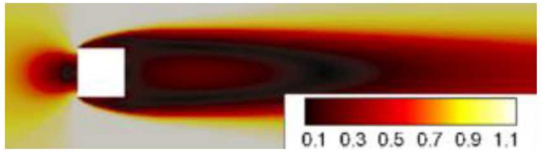
- Created spiking neural networks that mimic the human hippocampus's neurogenesis capability
- Developed adaptive memory management based on neurogenesis
- Developed future neuromorphic architectures for cyber and remote sensing applications



Neural (Hippocampus/Cortex) Inspired Computing

FY15 Early Career LDRD project: Identification of Markers of High RANS Uncertainty for Model Improvement in Engineering Flows

- Machine learned surrogate models to identify turbulent flow regimes

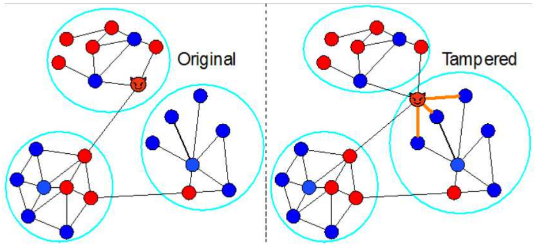


Fluid flow around a square cylinder:
Potential for fast NN pre-conditioning

FY16-18 Subsystem Reduced Order Modeling and Network Uncertainty Quantification

- Machine learned surrogate models used for >200X computational speed up

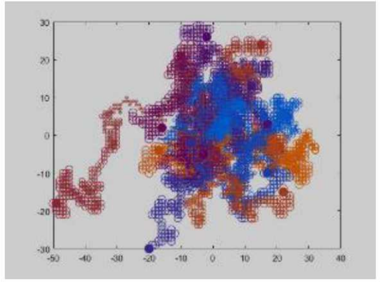
FY13-FY18 LDRD's to investigate Counter Adversarial Data Analytics (CADA) and Counter Adversarial Graph Analytics (CAGA)



Counter Adversarial Graph Analytics

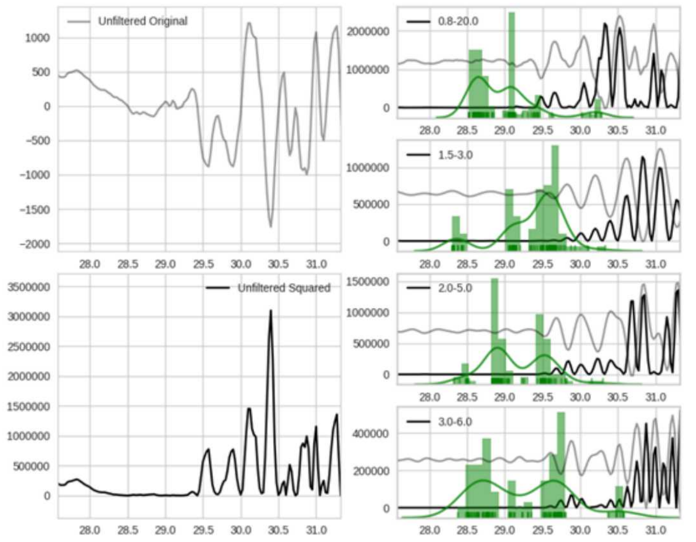
FY18 LDRD to solve partial differential equations using spiking neural networks

- Success would enable >100x speedup using neuromorphic accelerators in Exascale HPC

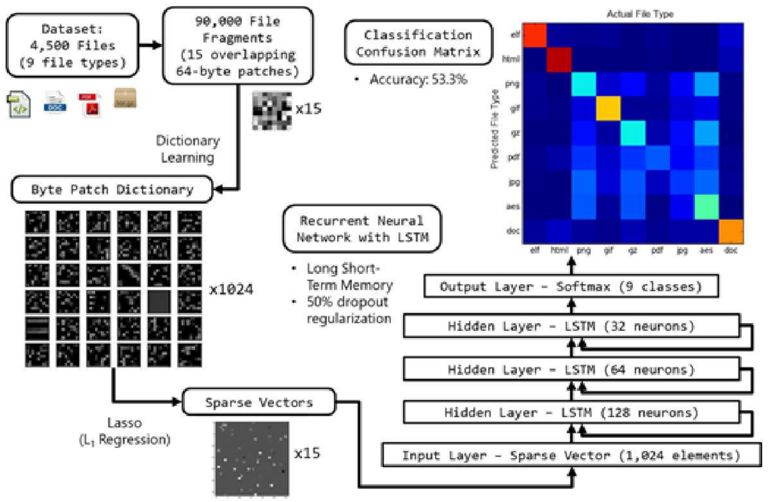


Random walk simulating a diffusion equation

Promising Machine Learning Impacts at Sandia

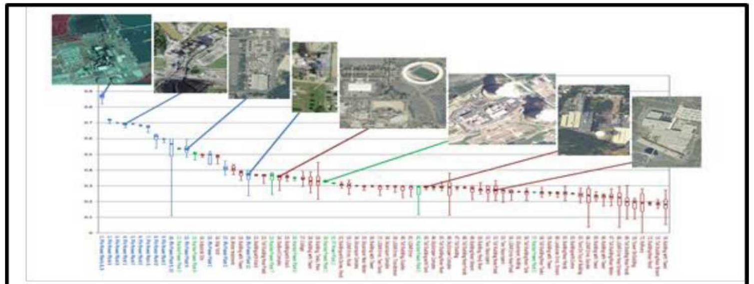


Machine Learning used to select the start of a seismic disturbance and determine its uncertainty.

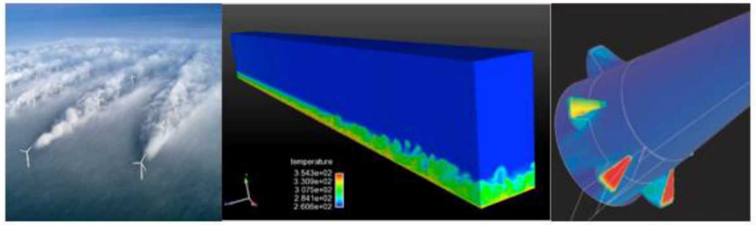


Implemented a neural-inspired architecture for tracking known threats in cyber network streams.

Machine Learning used to identify similar flight patterns in aircraft and identify anomalous flight trajectories.



Enabling user-driven search of wide-area overhead imagery via *geospatial-temporal semantic graphs*



Successfully used deep neural networks to predict quantities of interest (QoI) in turbulent flows more accurately than the current state-of-the-art.

Machine Learning used to detect and diagnose High Performance Computing performance variations.

New Mexico
Research Spotlight Forum

1/29/2019 Artificial Intelligence & Machine Learning

Uncertainty in Machine Learning

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Capability Overview

Sandia National Laboratories | THE UNIVERSITY OF NEW MEXICO | NM STATE UNIVERSITY | NEW MEXICO TECH SCIENCE • ENGINEERING • RESEARCH UNIVERSITY

SAND2019-0697 PE

ABOUT YOURSELF

Background:

- Ph.D. in Computer Science, Univ. of Massachusetts at Amherst, 2006
  Technical focus on machine learning
- Post doc at Stanford and Research Faculty at Arizona State through 2009
  Technical focus on learning in intelligent agent architectures
- Sandia National Laboratories, Center for Computing Research, starting in 2010
  Technical focus on uncertainty quantification for machine learning and human-data analytic systems

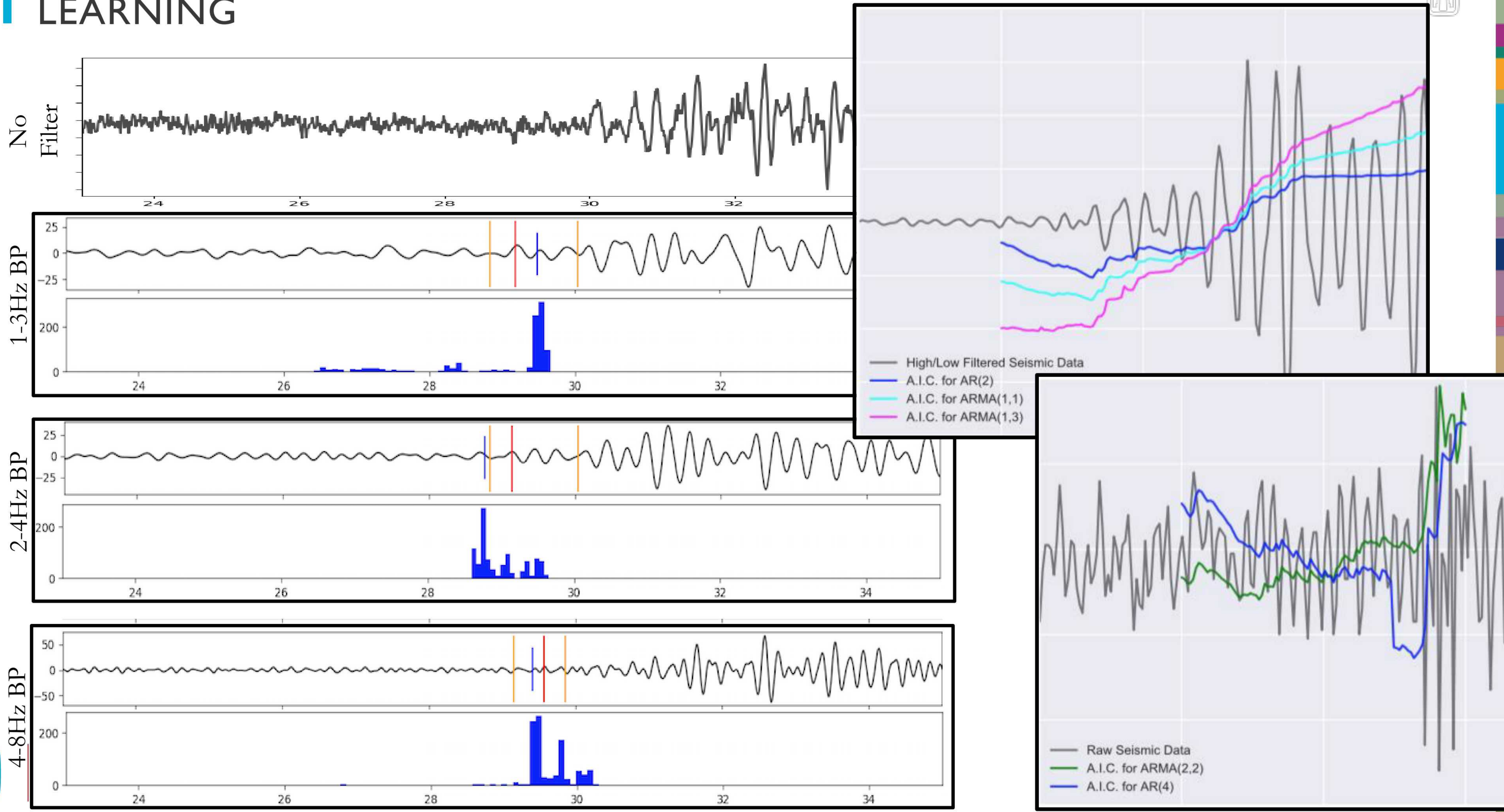
Research Areas:

- Uncertainty quantification for machine learning
  "Estimating the impact of data quality and preparation, algorithms, metrics and loss functions, and system parameters on machine learning models and the predictions they make."
- Human-data analytic systems
  "Incorporating the information needs and domain expertise into computational data analytics to improve the overall performance of the combined human-data system."

Keywords:

Machine learning, artificial intelligence, data analysis, decision making

CURRENT WORK IN ARTIFICIAL INTELLIGENCE / MACHINE LEARNING



ONGOING RESEARCH

Research topics comprise multiple topics based on a mix of internal and external funding.

- Activity Analysis
  - Construct a temporal model of objects and events (multimodal)
  - Discover similarities and patterns; Label known activities
  - Identify changes; make predictions about the future
  - Examples: Malls, network usage
- Modeling and Prediction of Scientific Data
  - Analyze data collected from many sensor types to predict future states or describe unobservable properties
  - Extensive use of sensor data, statistics, machine learning, and domain expertise
  - Comparison to scientific/theoretical models and predictions
  - Examples: Prediction of Arctic Sea Ice Concentration; Subsurface Rock Properties (Geothermal)
- Decision Support
  - Analyze data to determine if objects or situations are "normal"
  - Quantify the degree to which decision model is confident or within it's training
  - Examples: Malicious URL Detection, Quality Control

RESEARCH NEEDS

My work spans many domains, data types, and modeling methods.

I'm interested in students and collaborations that lead to principled solutions to practical applications.

Specific methods are less important than finding the most appropriate method and understanding its implications.

New Mexico Research Spotlight Forum

1/29/2019 Artificial Intelligence & Machine Learning

Large-Scale Neural Modeling with N2A

Fred Rothganger, SNL

Sandia National Laboratories is a multimission laboratory managed and operated by National Technology and Engineering Solutions of Sandia LLC, a wholly owned subsidiary of Honeywell International Inc. for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA0003525.

Capability Overview

Sandia National Laboratories

THE UNIVERSITY OF NEW MEXICO

NM STATE UNIVERSITY

NEW MEXICO TECH
SCIENCE • ENGINEERING • RESEARCH UNIVERSITY

SAND2019-0881 PE

ABOUT MYSELF

- PhD in Artificial Intelligence from UIUC. Thesis on 3D object recognition. Worked with robots.
- Current research in neural modeling methods and neuromorphic hardware.
- Department 1421 “Cognitive & Emerging Computing”
  - 18 Staff members, more than half are PhDs
  - Fields include: Neuroscience, Psychology, Computer Science, Electrical Engineering

Keywords:

Modeling & Simulation, AI, Neuroscience, Neuromorphic computing

CURRENT WORK IN ARTIFICIAL INTELLIGENCE / MACHINE LEARNING

N2A (“Neurons to Algorithms”) – Language and software tool for modeling large-scale neural systems.

- Object-oriented language
  - Each “part” is a set of ordinary differential equations.
  - A part is like a class. It can have any number of instances at runtime, each with its own distinct state.
- Suitable for modeling complex (as opposed to merely big) neural systems.
  - Many different kinds of parts, each with their own dynamics.
  - Many different kinds of interactions, each with their own rules for making connections.
  - Originally intended for modeling neural circuits (interactions among a set of neuron populations).
  - Goal is (eventually) to model the whole brain.
- Compiles to multiple targets, including supercomputers and several neuromorphic chips (SpiNNaker, STPU)

CURRENT WORK IN ARTIFICIAL INTELLIGENCE / MACHINE LEARNING

Other work…

Group Formation – Studying how human groups and hierarchies form, based on the hypothesis that the mechanisms are recursive (self-similar) across scales. Mining MMOG and social network data.

Moving Target Classification – Deep networks trained to classify objects based only on their movements over time. For example, distinguish between fighter and commercial aircraft.

Image recognition for web crawling

FUNDING SOURCES

Sandia Lab-Directed Research & Development (LDRD)

External government customers

RESEARCH NEEDS

Deep learning for image retrieval (like Google Images).

Draw on neuroscience literature to develop N2A neural circuit models.

New Mexico
Research Spotlight Forum

1/29/2019 Artificial Intelligence & Machine Learning

Machine Learning Applications in Electromagnetics

Christos Christodoulou
University of New Mexico
christos@unm.edu

Capability Overview

Sandia National Laboratories | The University of New Mexico | NM State University | New Mexico Tech Science • Engineering • Research University

Bio

- Ph.D. Electrical Engineering-North Carolina State University, 1985
- Dean, School of Engineering at UNM (2017-now)
- 20 years ay UNM

Over 550 papers in journals and conferences, 17 book chapters, 8 books, and several patents. Served as the major advisor for 31 Ph.D., 71 M.S. Students, 9 Post Doctoral Fellows,

Research areas: Smart antennas, neural networks and machine learning applications in electromagnetics, Cognitive Radio, Reconfigurable antennas and systems, RF/Photonic and high power microwave antennas.

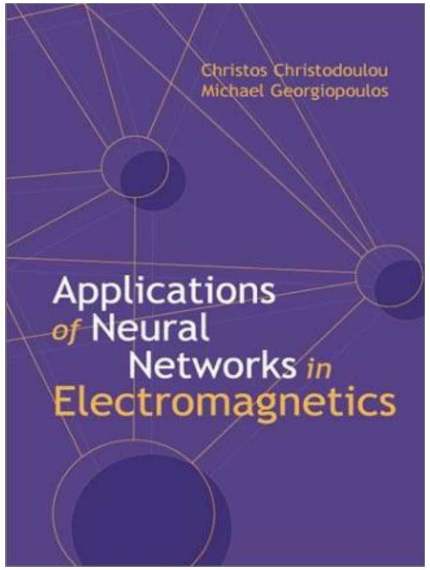
Keywords: Neural networks , Support Vector machines, reconfigurable systems, Cognitive radio

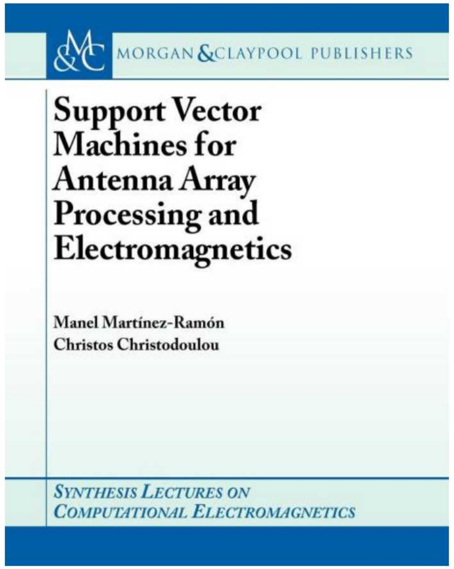
CURRENT WORK IN ARTIFICIAL INTELLIGENCE/ MACHINE LEARNING

1. Support Vector Machines (Radar Applications, Smart Antennas, and Cognitive Radio)
2. Neural networks (back prop, Radial basis functions, ARTMAP) in adaptive beam forming and Angle of Arrival Estimation
3. Neural Networks in Estimating failures of antennas elements in phased arrays
4. Neural Networks in Reconfigurable Antennas
5. Support Vector Machines in Randomized Antenna arrays (cluster of satellites)

Books and Previous Work with SNL

2001





2006

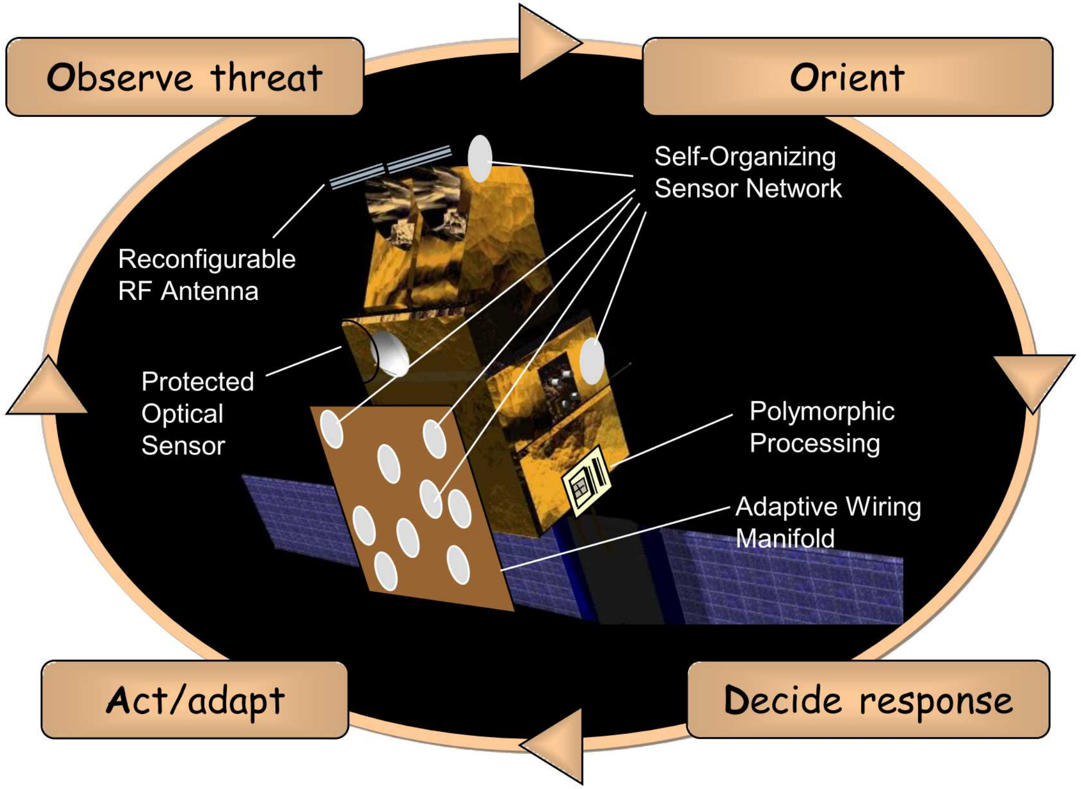
Machine Learning Methods for CDMA Power Control and Direction of Arrival Estimation (Judd Rowher) – 2003

RF Channel Characterization for Cognitive Radio Using Support Vector Machines (Tom Atwood) - 2009

Reconfigurable Systems/Spacecraft

Adaptive avionics for:

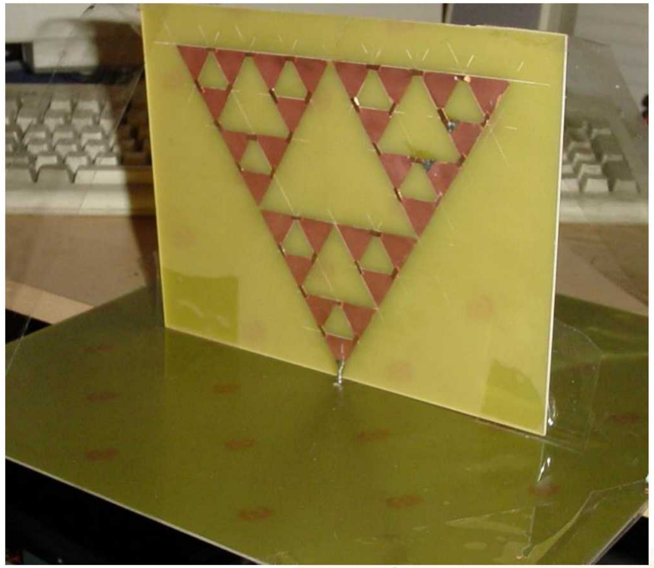
- *Rapid payload integration*
- *Space system reconfiguration*
- *Systems on-orbit protection*



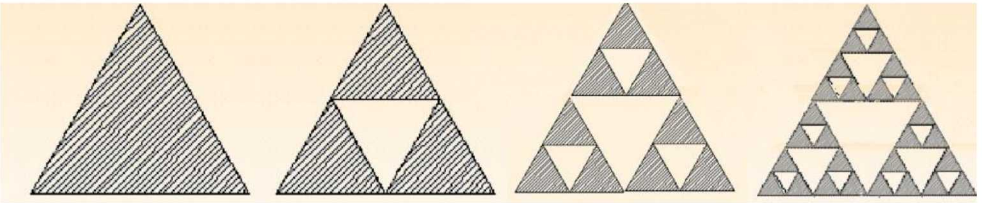
- *Self-organizing sensor network*
- *Adaptive MEMS-based wiring manifold*
- *Polymorphic processors*
- *Reconfigurable RF system*
- *Self-aware cognitive software*

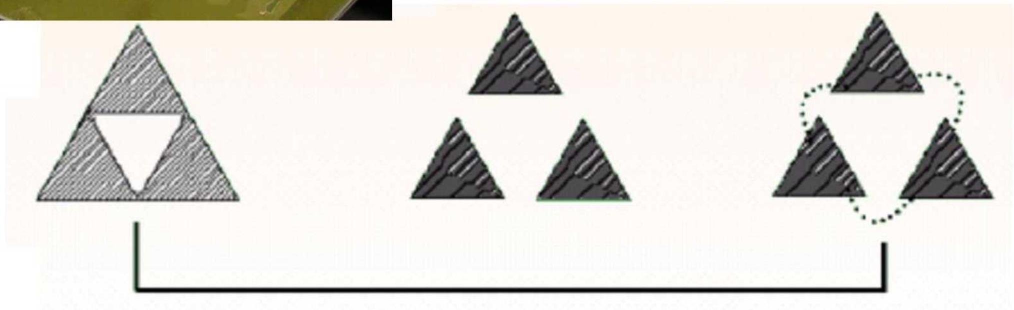
James Lyke

Example: Reconfigurable fractal Antenna



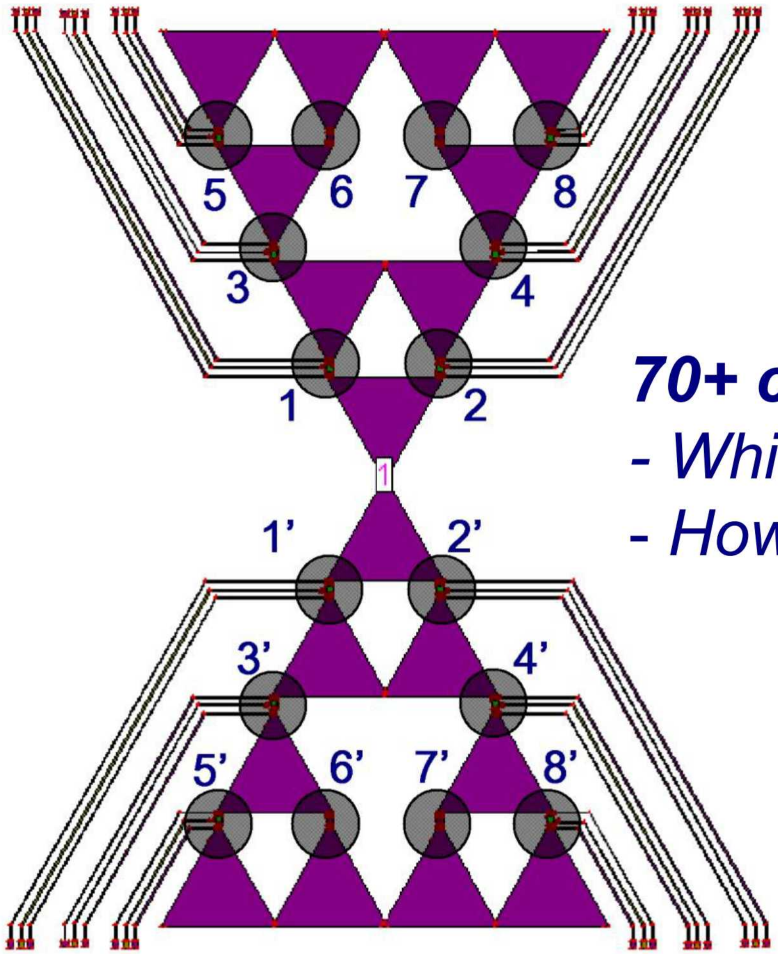
Triangular Patches & MEMS:





Connected Separated Connected with
MEMS enabled RF-MEMS switches

How can we tell what switches should be on for specific frequencies?

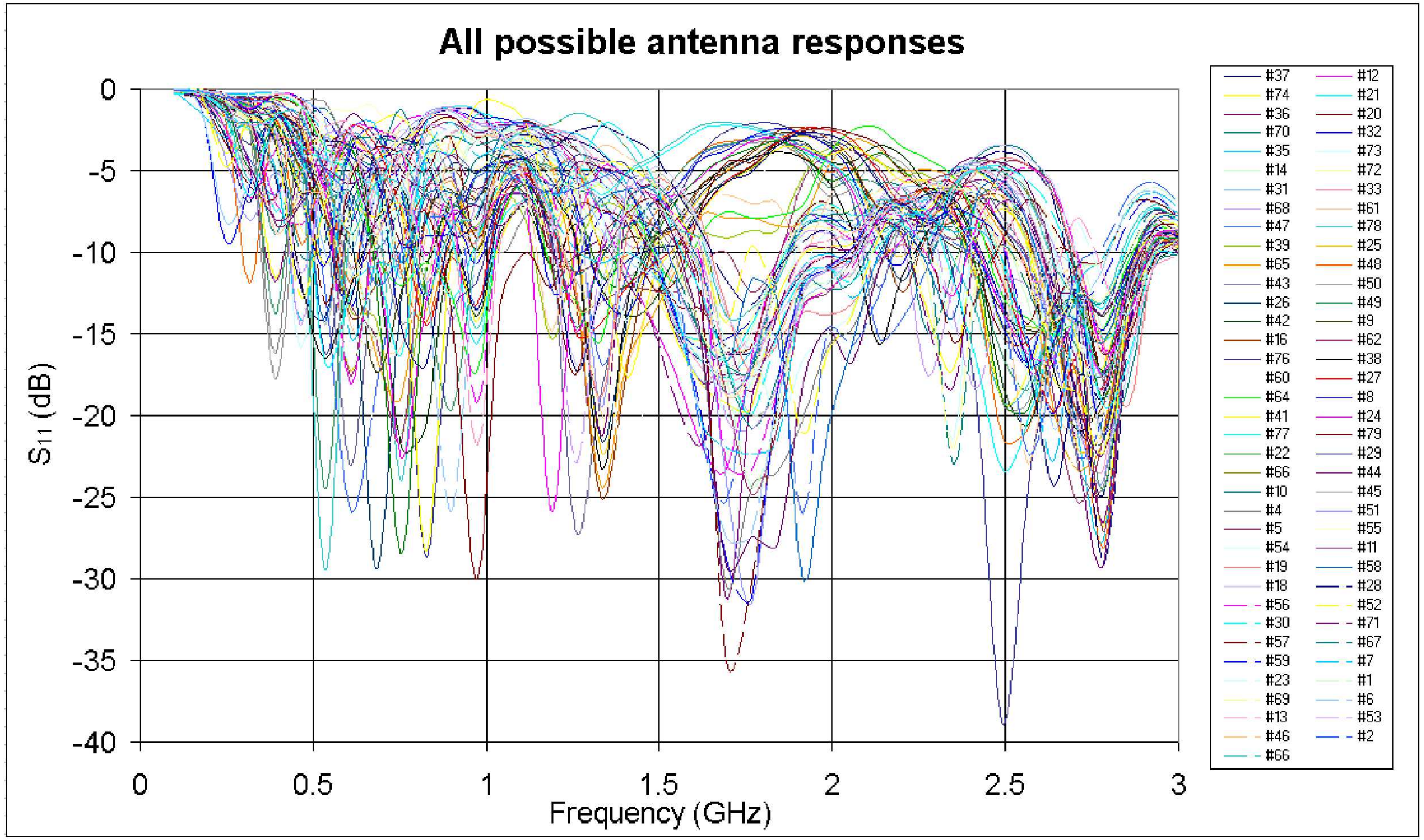


70+ configurations depending on:

- Which elements are active

- How they are connected / fed

Results – Self-Organizing Map

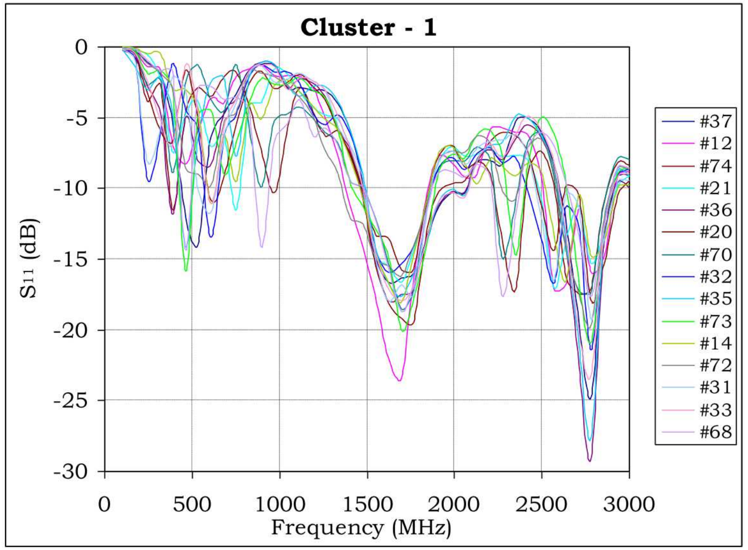


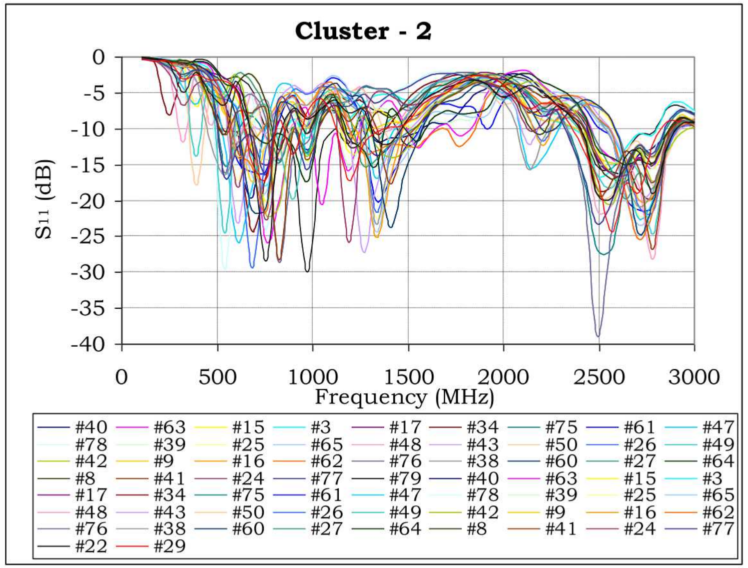
We Use Neural Networks ??

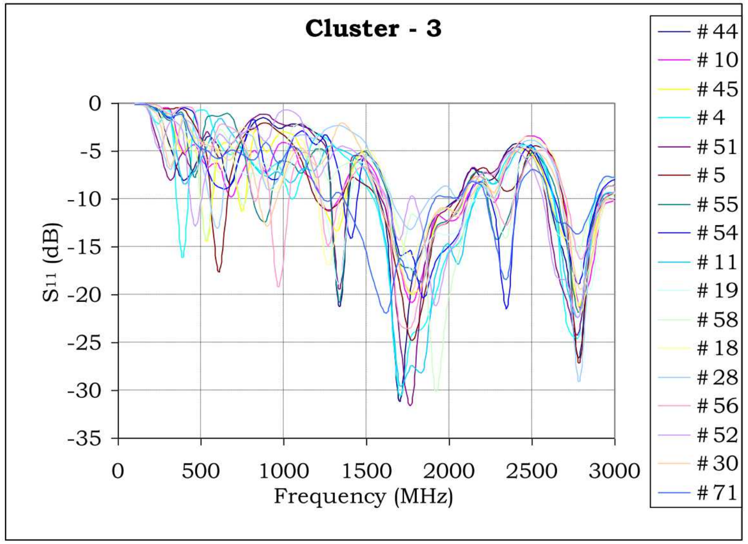
Neural Networks can be applied because:
- Closed-form solution does not exist and trial-and-error methods are the only approaches to solve the problem
- Enough measured data can be obtained to train the NN

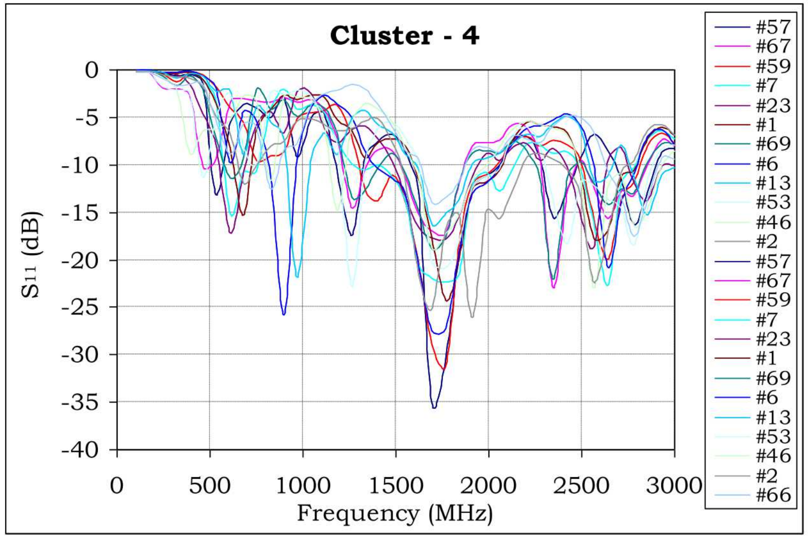
- **Fabricated & measured a prototype**
- **Established a ‘training database’**
- **Trained a NN**
- **Use NN for faster antenna synthesis**

Results – Self-Organizing Map

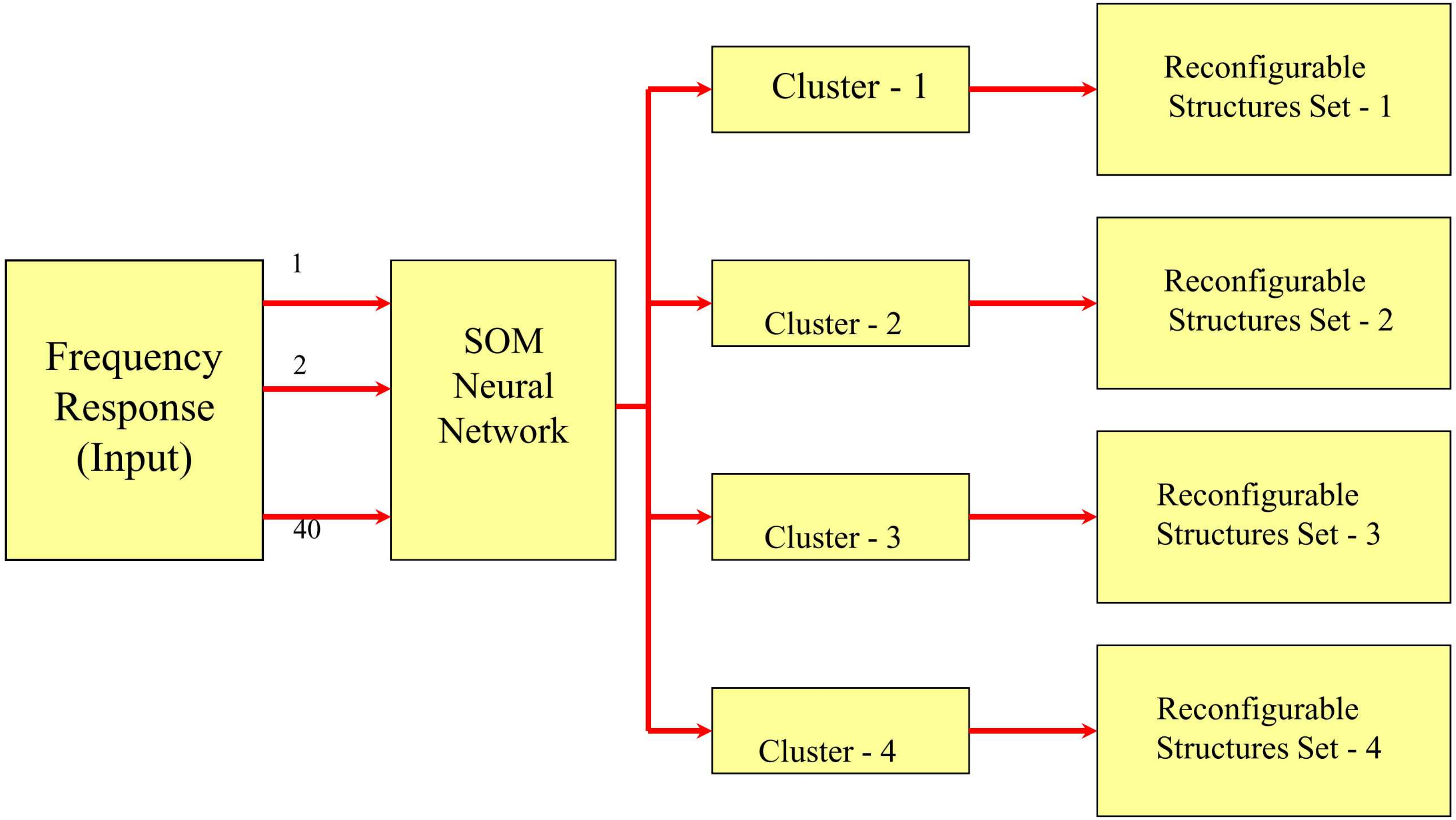




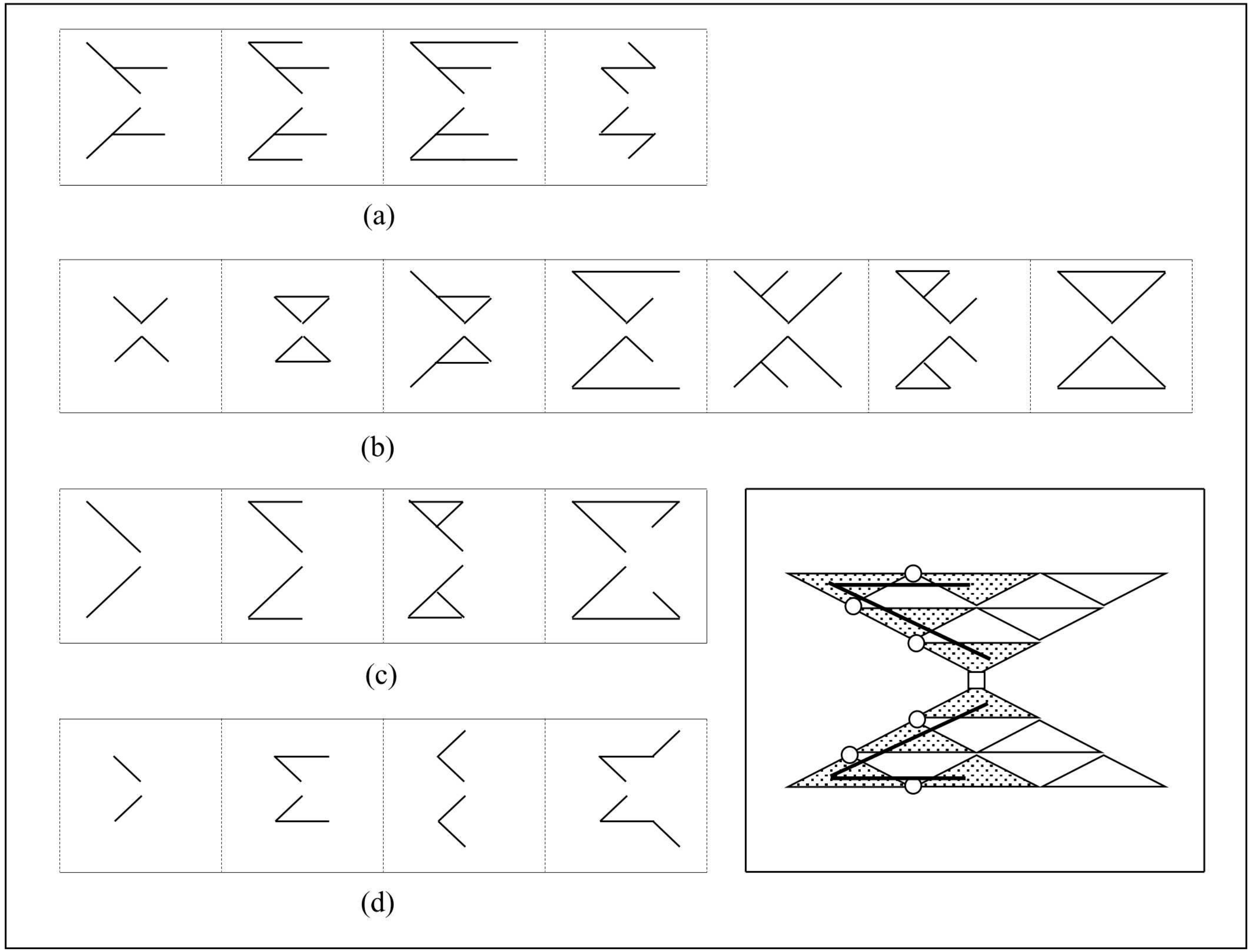




Reconfigurable antenna modeling



Reconfigurable antenna modeling

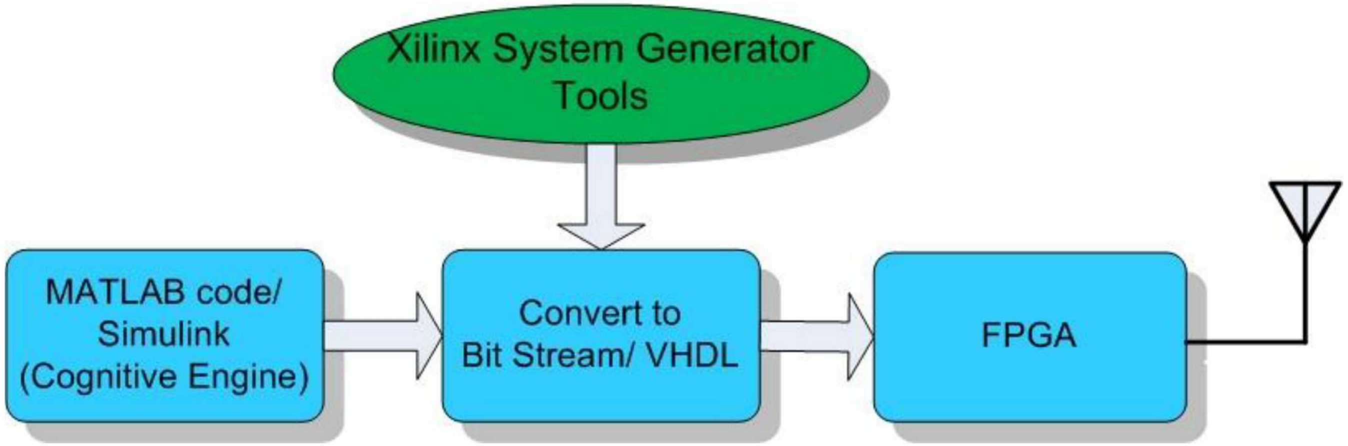


Neural Network Implementation on FPGAs

✓ A NN is trained to associate all the different configurations of a reconfigurable antenna with its different operating frequencies

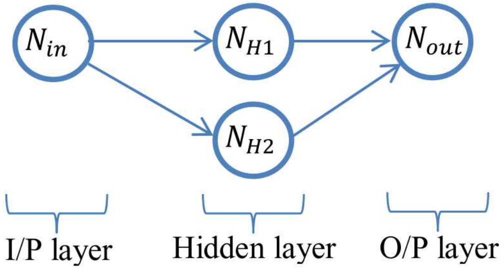
✓NN is built and trained in Matlab Simulink

✓After the weight adjustment process of the NN, a Xilinx system generator creates the NN VHDL code to be used to control an FPGA



✓ cognitive engine

NN Modeling of a Reconfigurable Filtenna

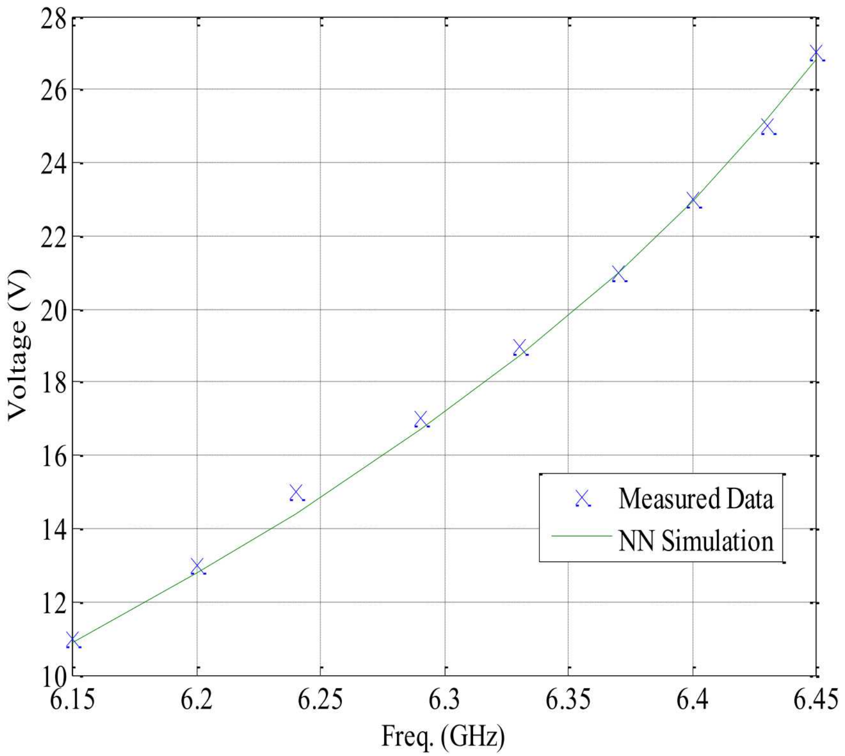


Iterations	3
Input Neurons	1
Output Neurons	1
Hidden Layers	1
Hidden Neurons	2

E. Al-Zuraiqi, Y. Tawk, H. Pollard, and C. G. Christodoulou, "Controlling reconfigurable antennas via neural network embedded into an FPGA," *IEEE International Symposium on Antennas and Propagation (APS-URSI),* July 2012.

NN Modeling of a Reconfigurable Filtenna

Freq. (GHz)	Measured voltage (V)	NN simulated voltage (V)
6.15	11	10.89
6.2	13	12.78
6.24	15	14.41
6.29	17	16.69
6.33	19	18.74
6.37	21	20.97
6.4	23	22.97
6.43	25	25.23
6.45	27	26.82



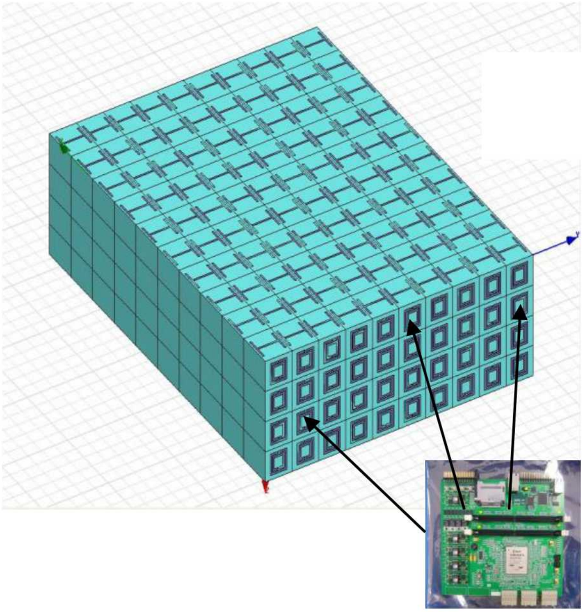
E. Al-Zuraiqi, Y. Tawk, H. Pollard, and C. G. Christodoulou, "Controlling reconfigurable antennas via neural network embedded into an FPGA," *IEEE International Symposium on Antennas and Propagation (APS-URSI),* July 2012.

NN-FPGA- Reconfigurable Filtenna

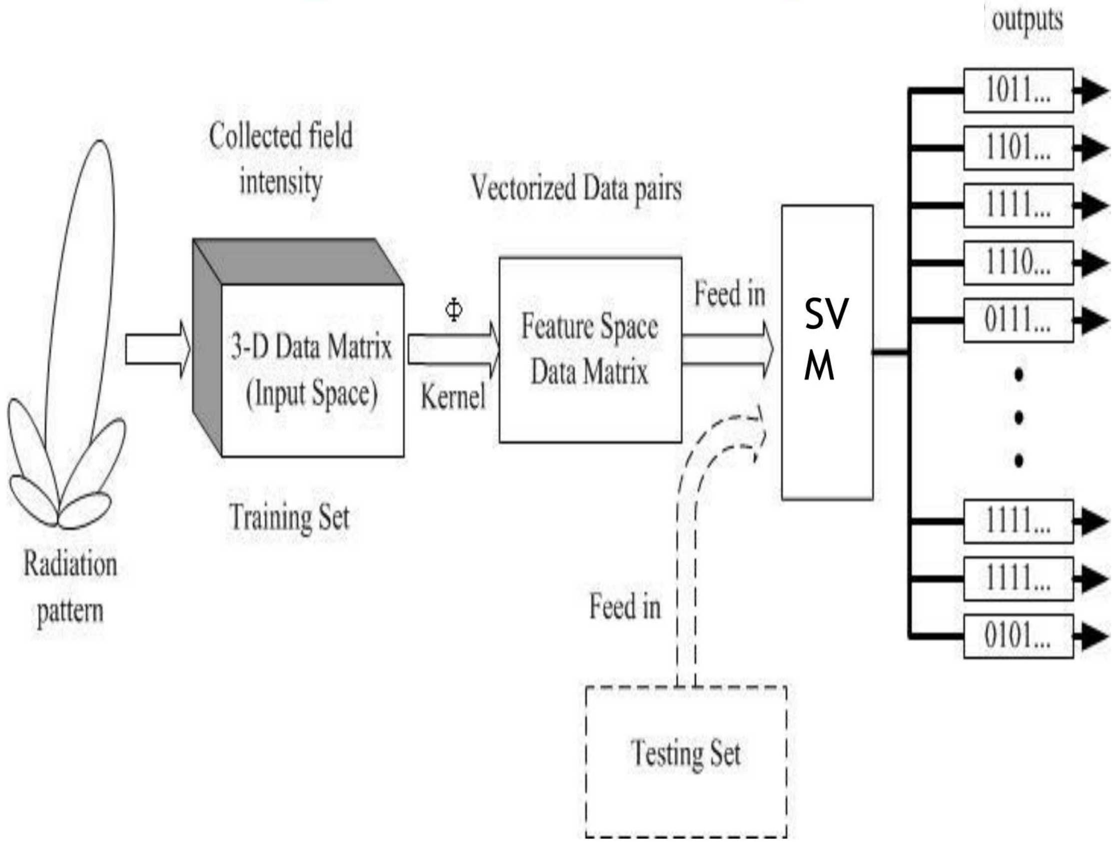
See Video "Slide 70"

E. Al-Zuraiqi, Y. Tawk, H. Pollard, and C. G. Christodoulou, "Controlling reconfigurable antennas via neural network embedded into an FPGA," *IEEE International Symposium on Antennas and Propagation (APS-URSI),* July 2012.

Reconfigurable metamaterials



Fault Diagnostics of an Array Antenna



Funding Sources

1. AFRL
2. AFOSR
3. NASA
4. Navy
5. ARL
6. Rdtech
7. Bluecom Systems
8. Virtual EM
9. Honeywell

New Mexico Research Spotlight Forum

1/29/2019 Artificial Intelligence & Machine Learning

Machine Learning & Artificial Intelligence in Cognitive Communications: Spectrum Situational Awareness (SSA), Signals Intelligence (SIGINT) and Cognitive GPS

Dr. Sudharman K. Jayaweera

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Communications and Information Sciences Lab (CISL)
ECE Department
University of New Mexico.
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Founder, President & CEO
Bluecom Systems & Consulting LLC
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Capability Overview

Sandia National Laboratories | THE UNIVERSITY OF NEW MEXICO | NM STATE UNIVERSITY | NEW MEXICO TECH SCIENCE • ENGINEERING • RESEARCH UNIVERSITY

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ABOUT YOURSELF

Brief biography:

- PhD, Princeton University.
- Founder, President and CEO of BLUECOM SYSTEMS LLC.
- Professor in Electrical and Computer Engineering at the UNM
- National Academy of Sciences National Research Council (NRC) Senior Fellow at the Naval Postgraduate School, Monterey, CA, 2013.
- Member of the technical staff at the US Wireless Corporation in San Ramon, CA, 1998-1999.
- Editor, IEEE Transactions on Wireless Communications.

- Research areas: Cognitive radios, cognitive GPS, cooperative communications, RF spectrum situational awareness, deep/machine learning, game theory, machine learning for autonomous reconfigurable space platforms, wireless communications, information theory, statistical signal processing.
- Research group interests, size and demographics: See last slide

Keywords:

Cognitive radios, cognitive GPS, cooperative communications, RF spectrum situational awareness, deep/machine learning, machine learning for autonomous reconfigurable space platforms, game theory, information theory, wireless communications.

From SDR to Cognitive Radio

Conventional Radio

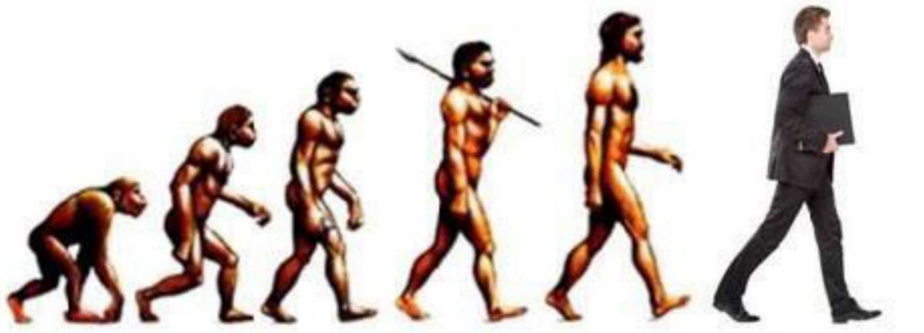
- Can support multiple, but fixed, number of services chosen at the time of design
- Reconfigurability decided at the time of design

Software Defined Radio

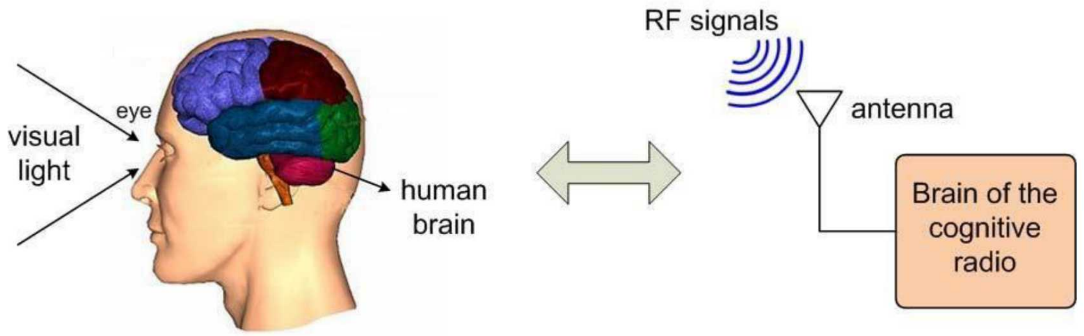
- Allow supporting multiple systems, protocols and interfaces by changing software programs
- When and how to reconfigure are probably user-determined.

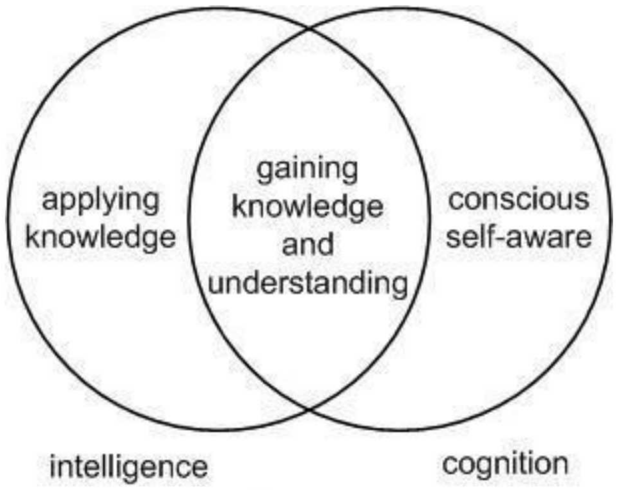
Cognitive Radio

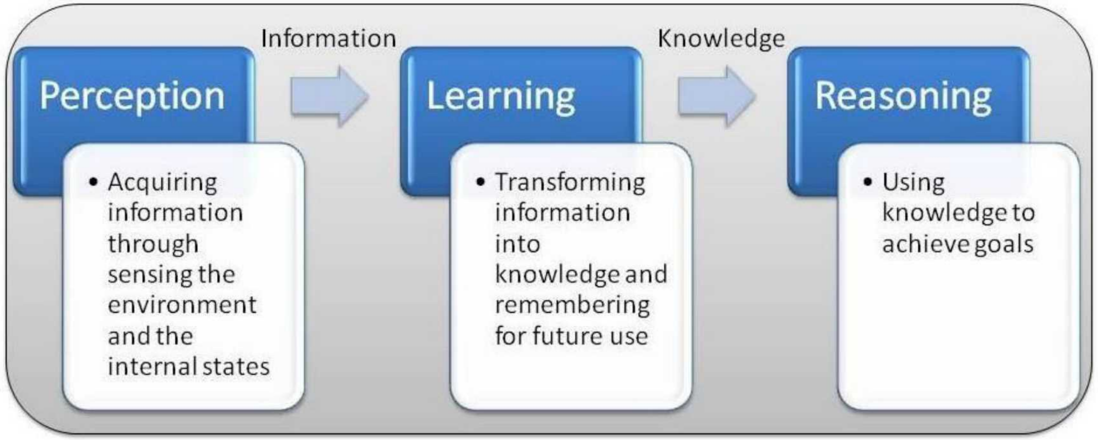
- SDR's with an independent brain of its own.
- When and how to reconfigure is decided by the radio itself!



Wideband Autonomous Cognitive Radios: Intelligent and Self-Aware

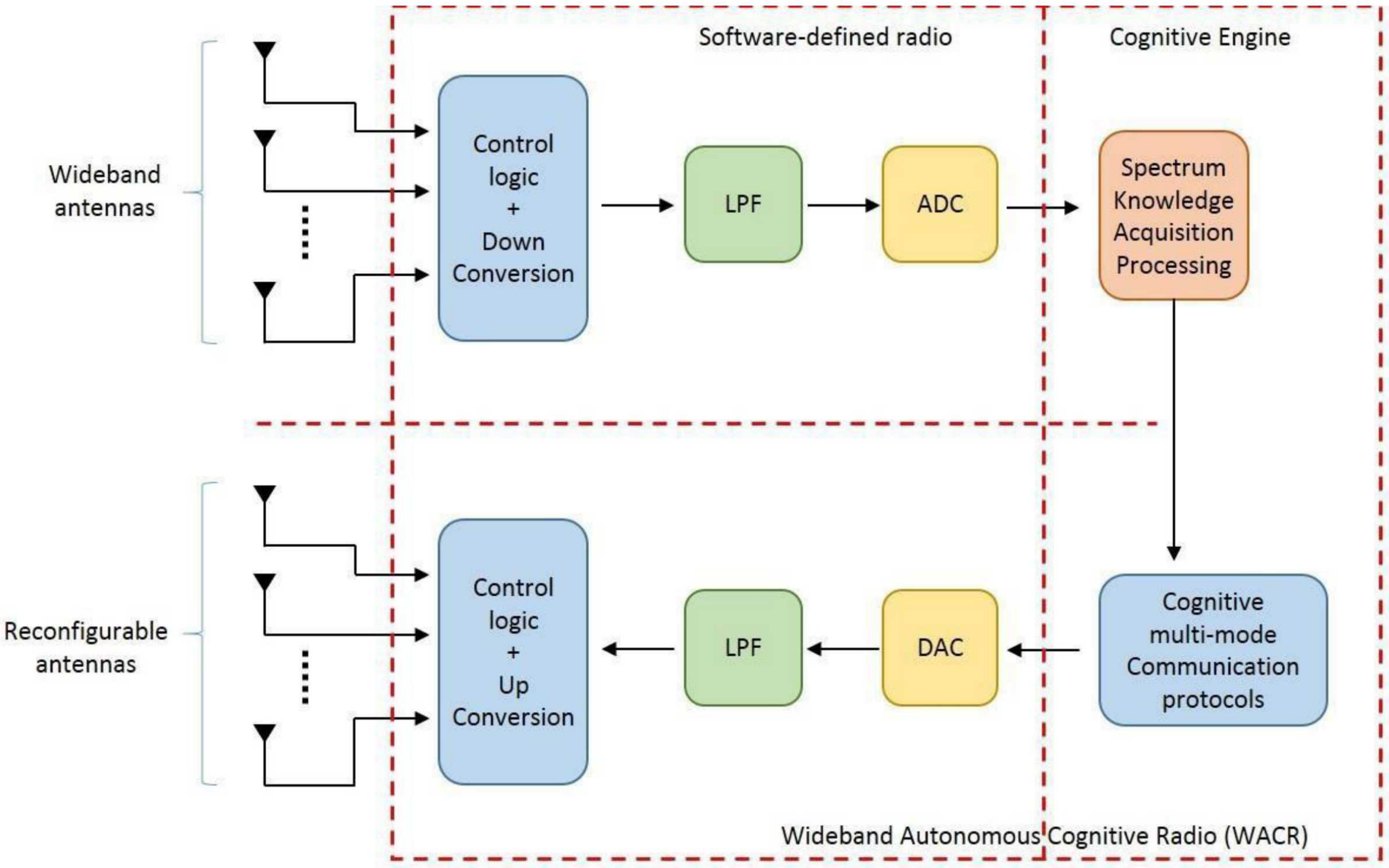




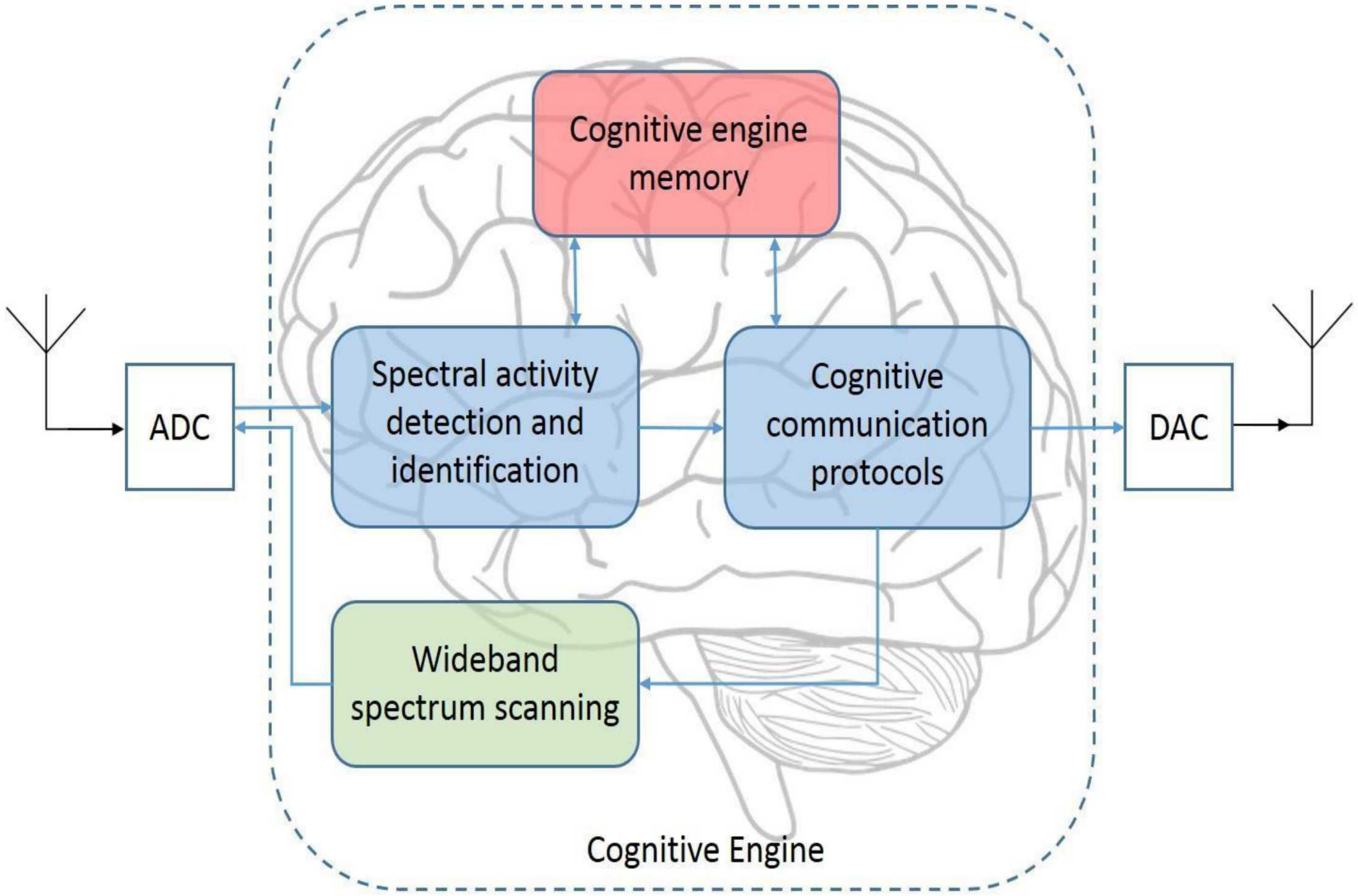


S. K. Jayaweera, "Signal Processing for Cognitive Radios", John Wiley & Sons, Hoboken, NJ, USA. 2014

Wideband Autonomous Cognitive Radio Architecture

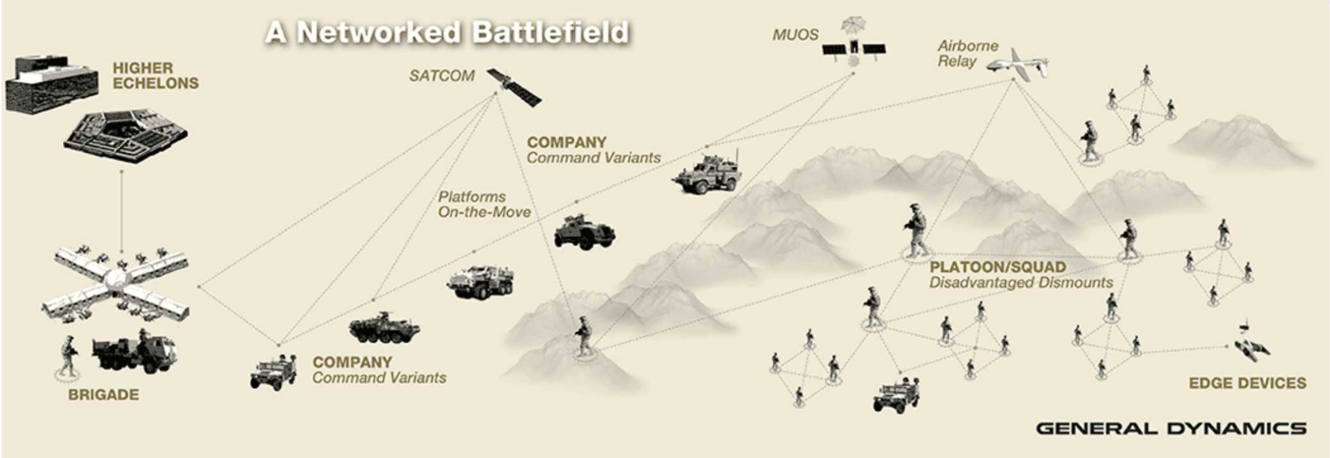


RadioBOT Technology (Cognitive Engine = The Brain)



DoD Applications of WACRs

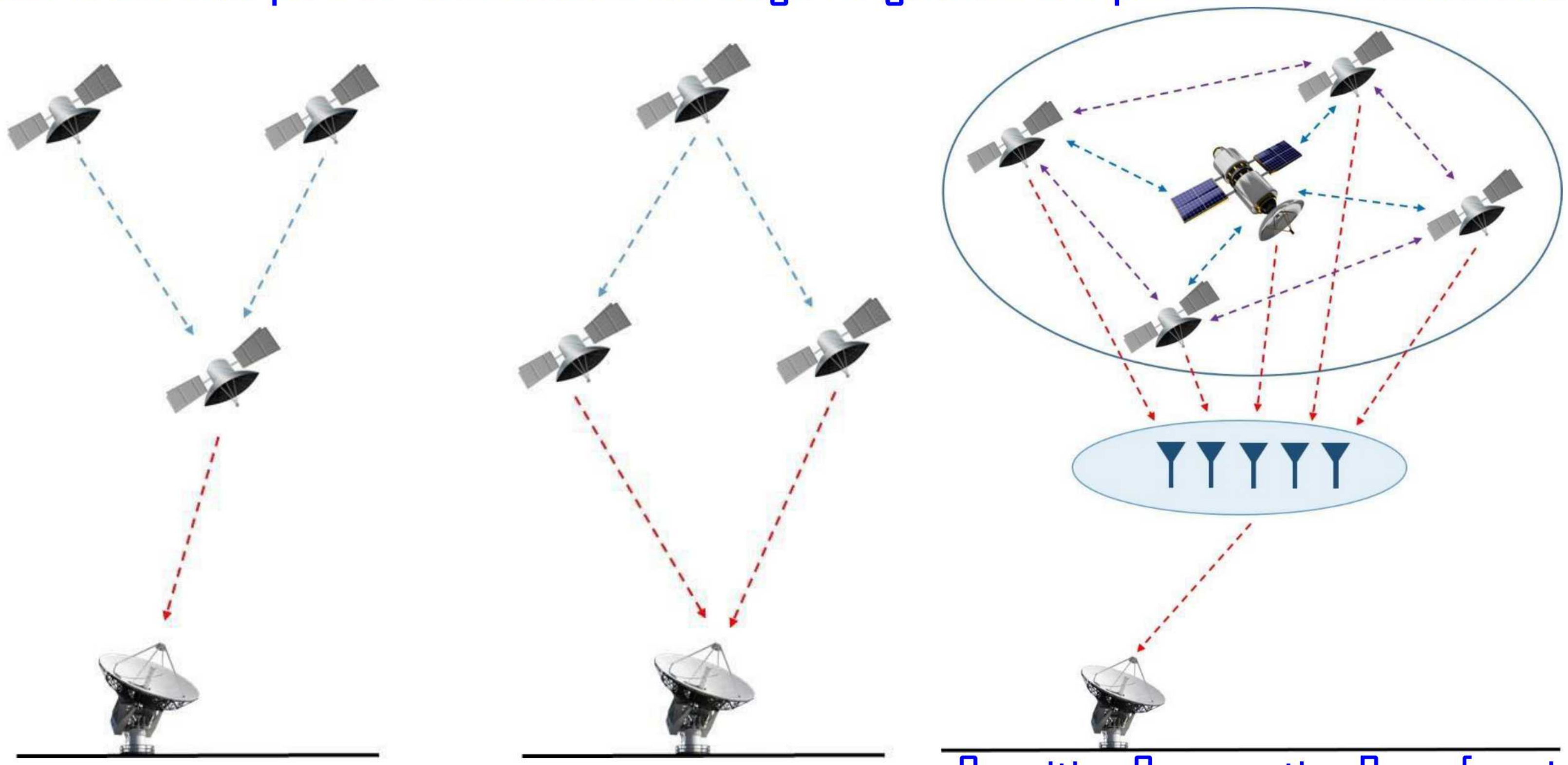
- Cognitive jamming and anti-Jamming
- Cognitive networking of radios to support warfighters in battlefield
- Cognitive cooperative communications among autonomous platforms
  - Terrestrial, air-borne or space.



- Spectrum-aware and spectrally-agile multi-mode/multi-band radios for messaging/communications in T&E scenarios
- Robust and Reliable communications in the presence of RFI
- Spectrum-agile Communications
- Cognitive Global Positioning Systems (Cognitive GPS)
- Next Generation Cognitive Global Navigation Satellite Systems (C-GNSS)

Cognitive Radios in Space: Cognitive Cooperative SATCOM

Clusters of CubeSat networks may cooperate to overcome interference, jamming and transmit power limitations through cognitive cooperative communications

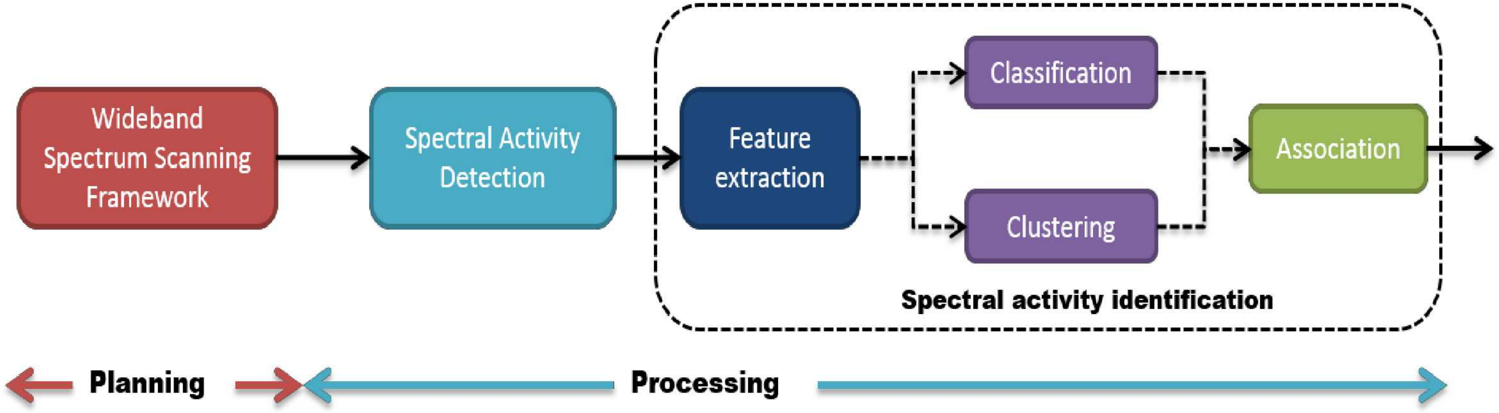


Cognitive Cooperative Relaying

Cognitive Cooperative Beamforming

S. K. Jayaweera, "Wideband Autonomous Cognitive Radios for Networked Satellite Communications", Final Project Report, NASA STTR Phase II, Bluecom Systems and Consulting, Oct. 2018.

Spectrum Knowledge Acquisition for spectrum situational awareness

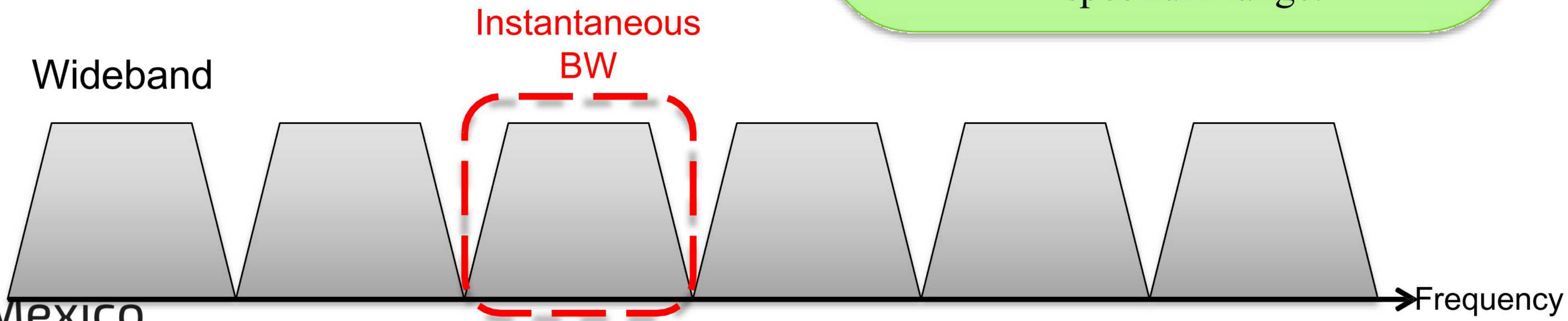


Wideband Spectrum Scanning

Spectrum awareness procedure

Wideband spectrum scanning
↓
Spectral activity detection
↓
Signal classification

- Hardware constraints limit the instantaneous sensing bandwidth of most state-of-the-art software-defined radio (SDR) platforms to about 100MHz.
- There is a need to design an efficient scheme to achieve real-time sensing over a wide spectrum range.



Spectral Activity Detection

Spectrum awareness procedure

Wideband spectrum scanning

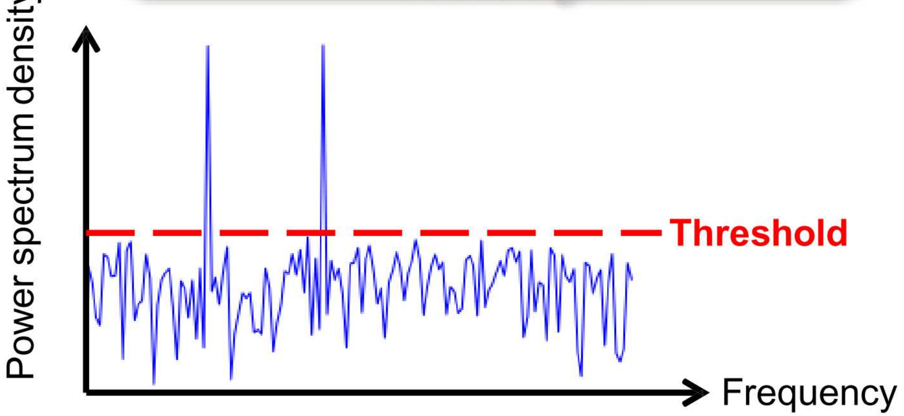
↓

Spectral activity detection

↓

Signal classification

- Detection can be performed in spectral-domain to detect active signals at arbitrary frequencies.
- Any power spectral activity above this threshold is considered as an active signal.



Signal Classification & Identification

Spectrum awareness procedure

Wideband spectrum scanning

↓

Spectral activity detection

↓

Signal classification →

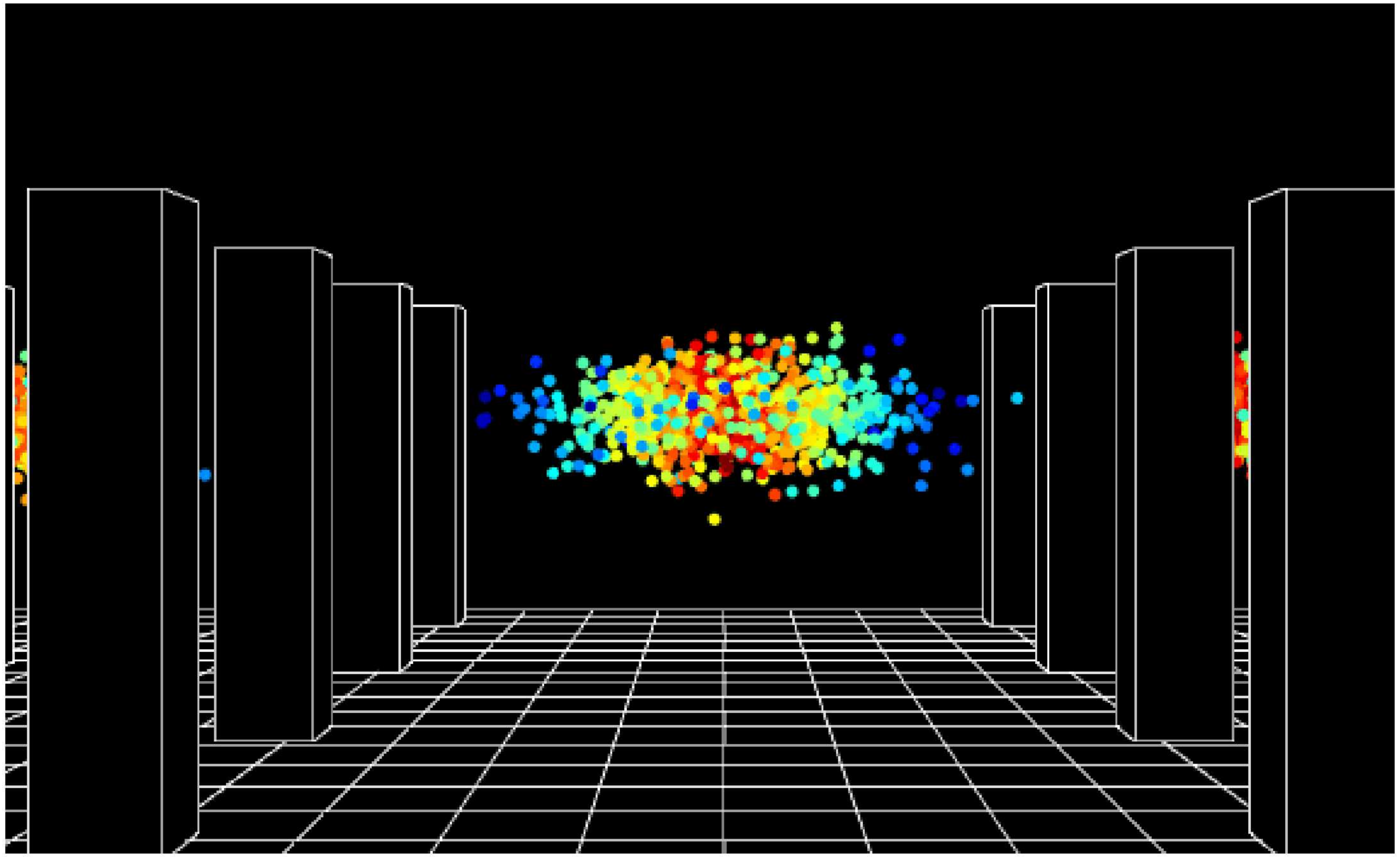
- Detected signals may belong to different radio systems.
- Extract suitable features on-the-fly.
- Classify, associate and identify signals.

Classification

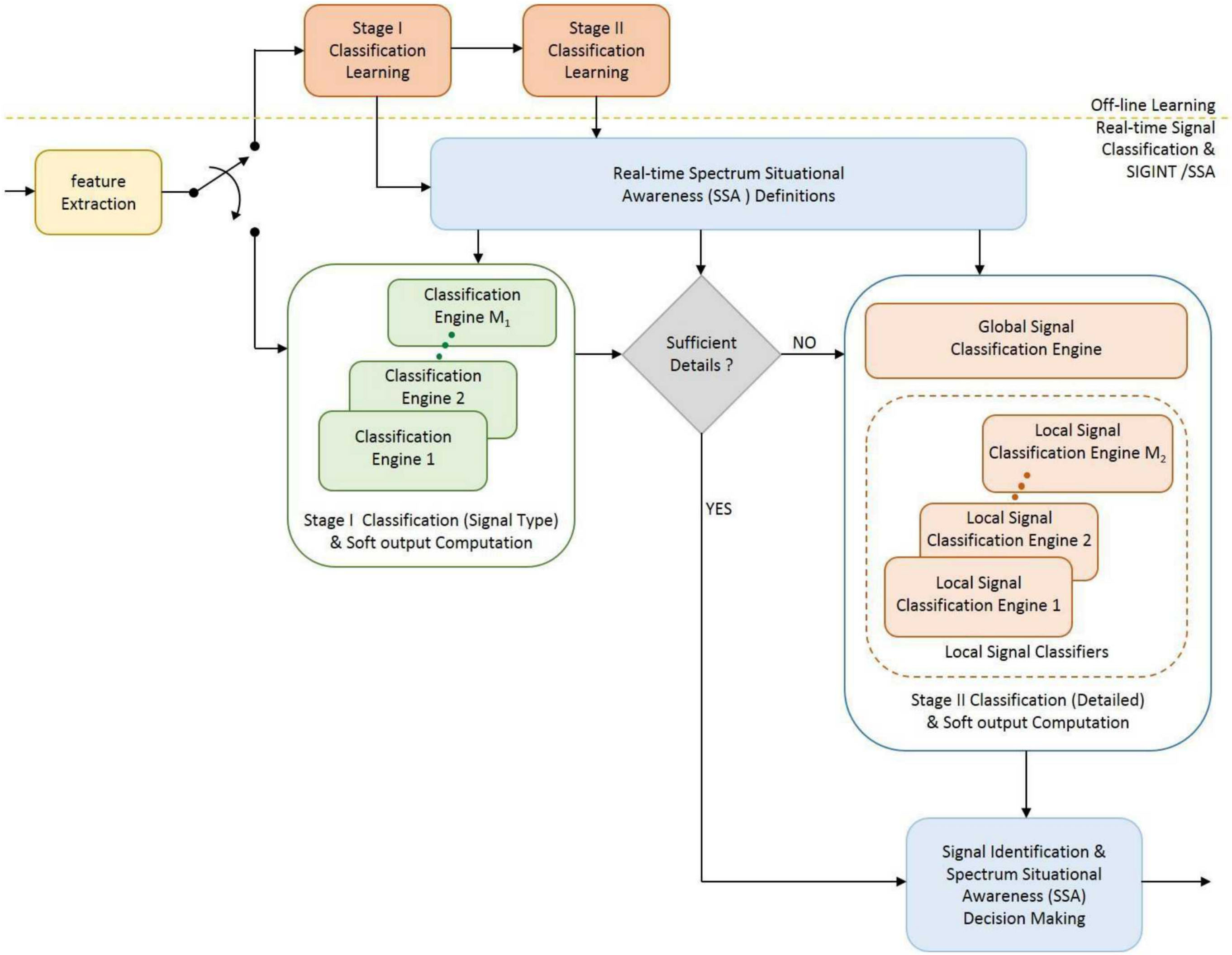
Wi-Fi Bluetooth Mobile … Others

RF Spectrum Situational Awareness

- Monitor
- Map
- Comprehend
- Act

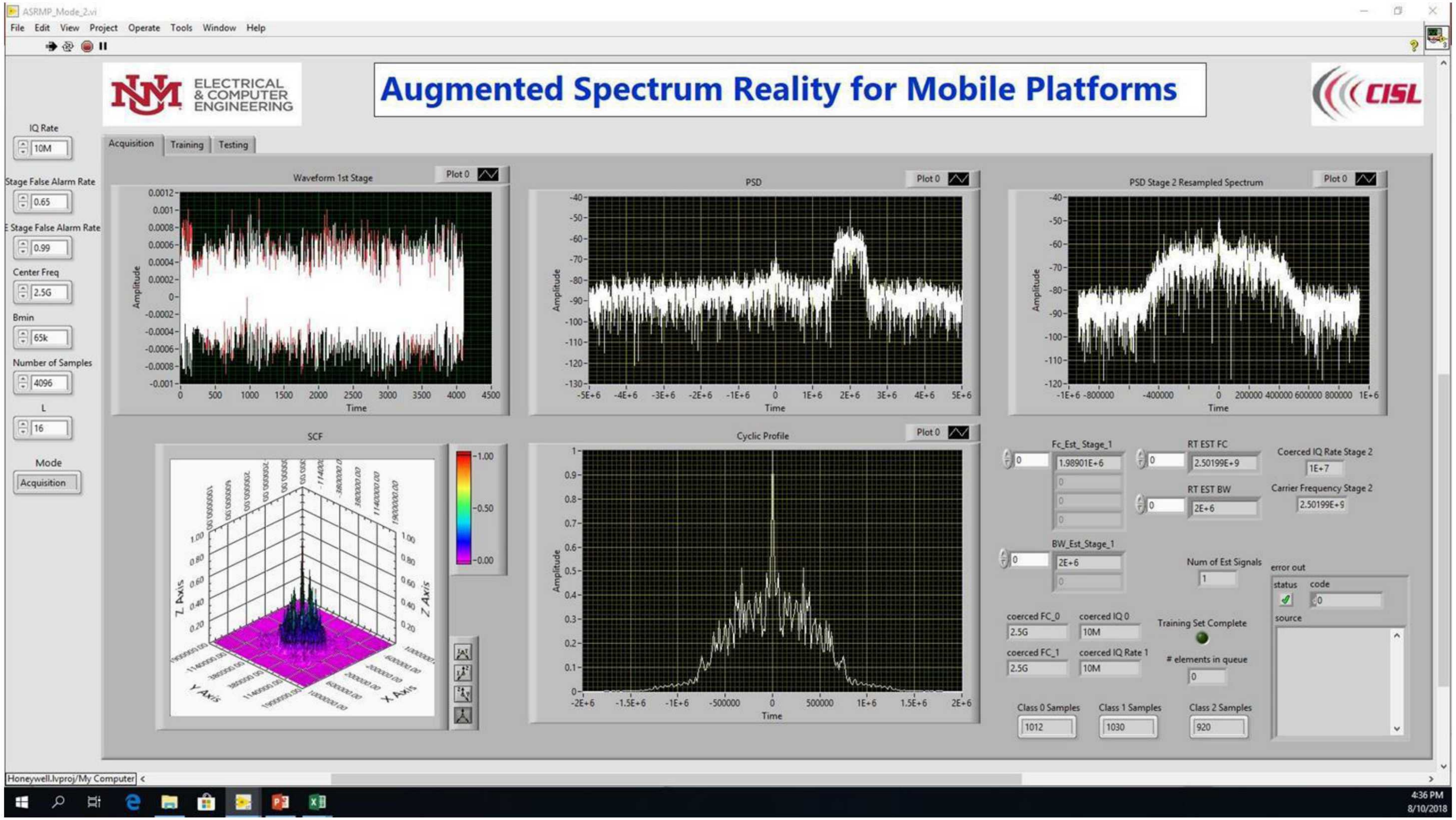


Hierarchical SSA Tool



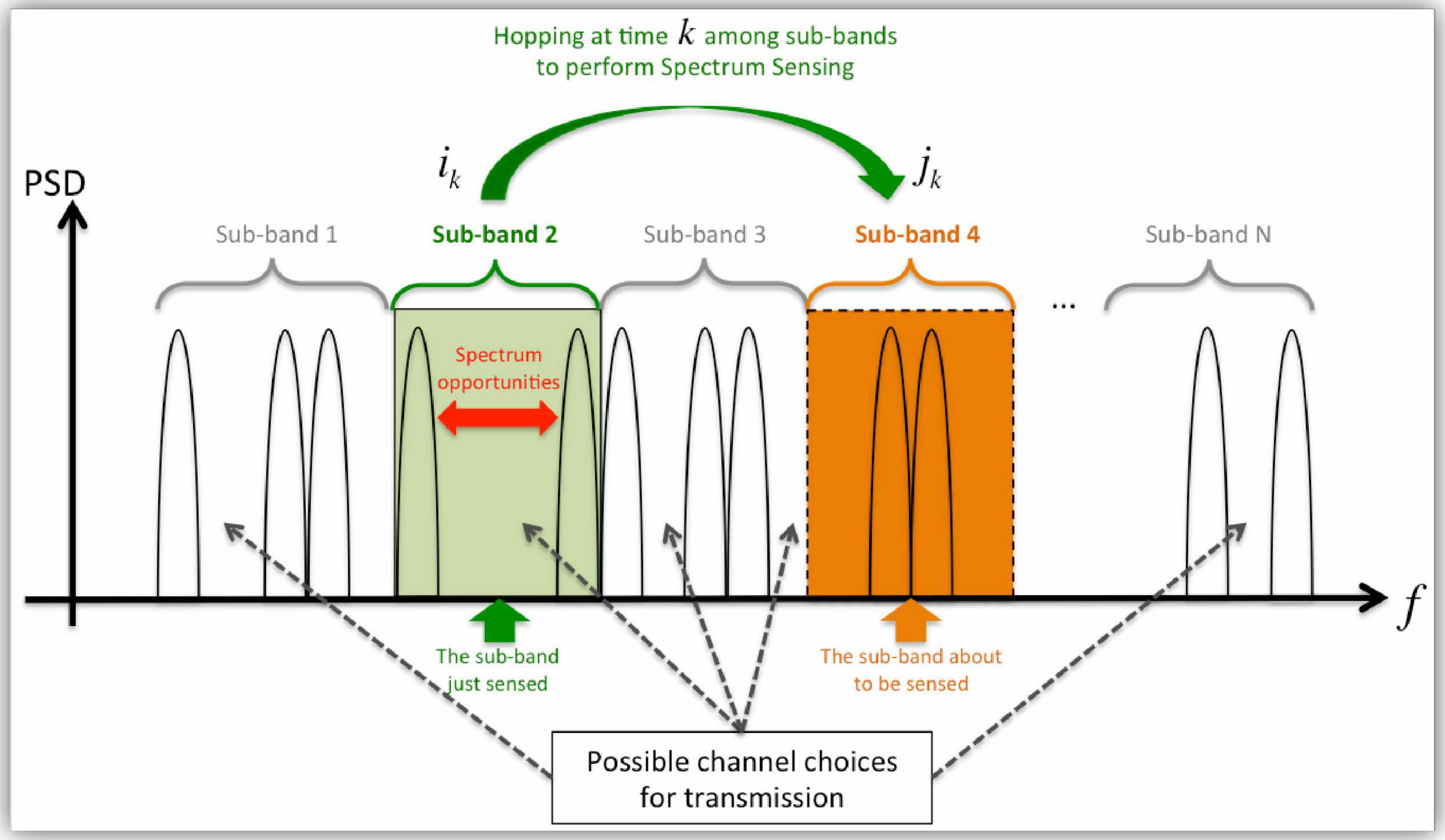
S. K. Jayaweera and M. A. Aref, "Cognitive Engine Design for Spectrum Situational Awareness and Signals Intelligence", 21st IEEE International Symposium on Wireless Personal Multimedia Communications (WPMC'18), Chiang Rai, Thailand, Nov. 2018.

SSA Tool for Augmented Spectrum Reality: Testing Mode



Signal classification Engine: Deep Learning

Spectrum Agility & Cognitive Anti- jamming Communications

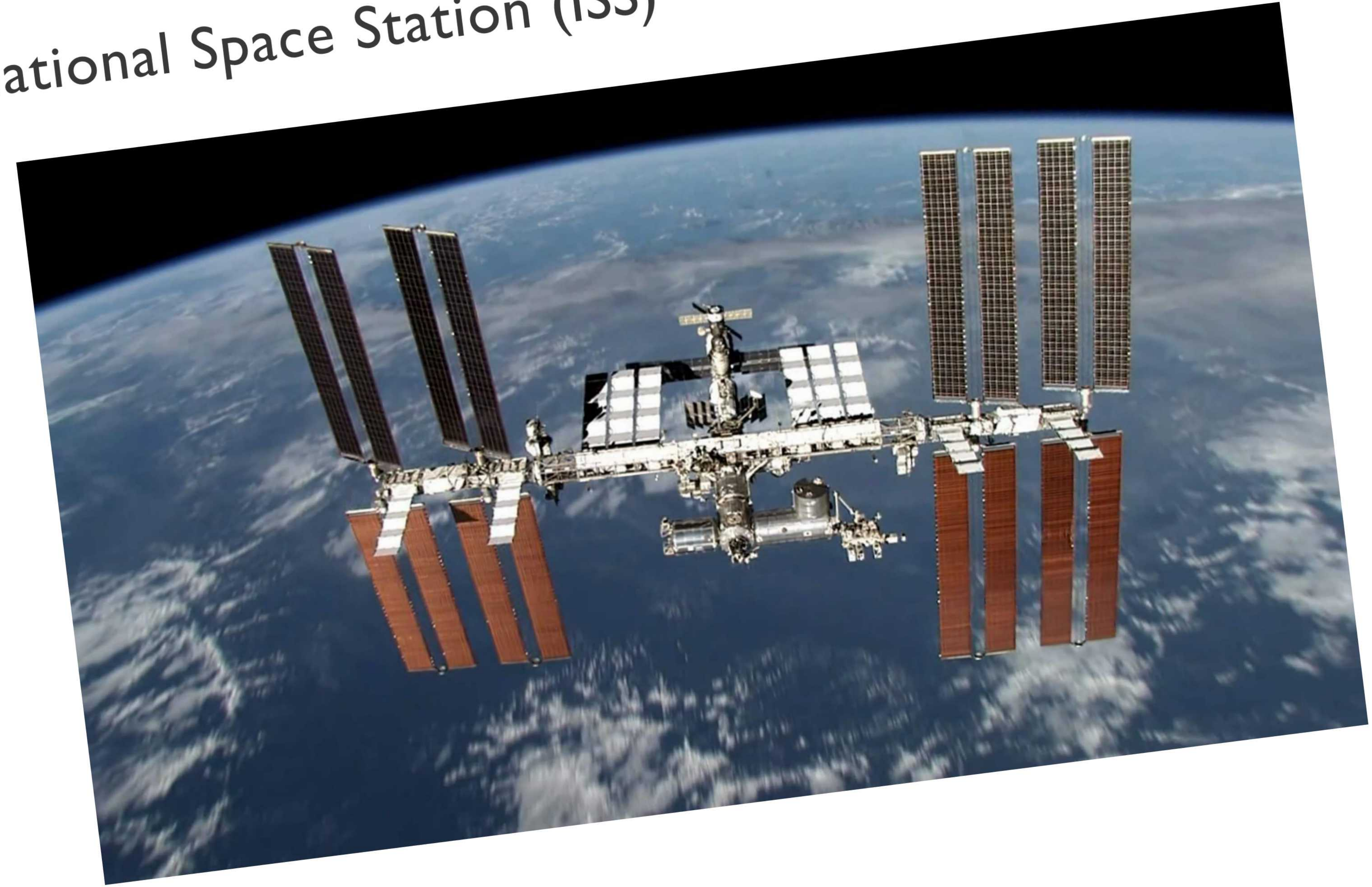


Avoid interference & jammers

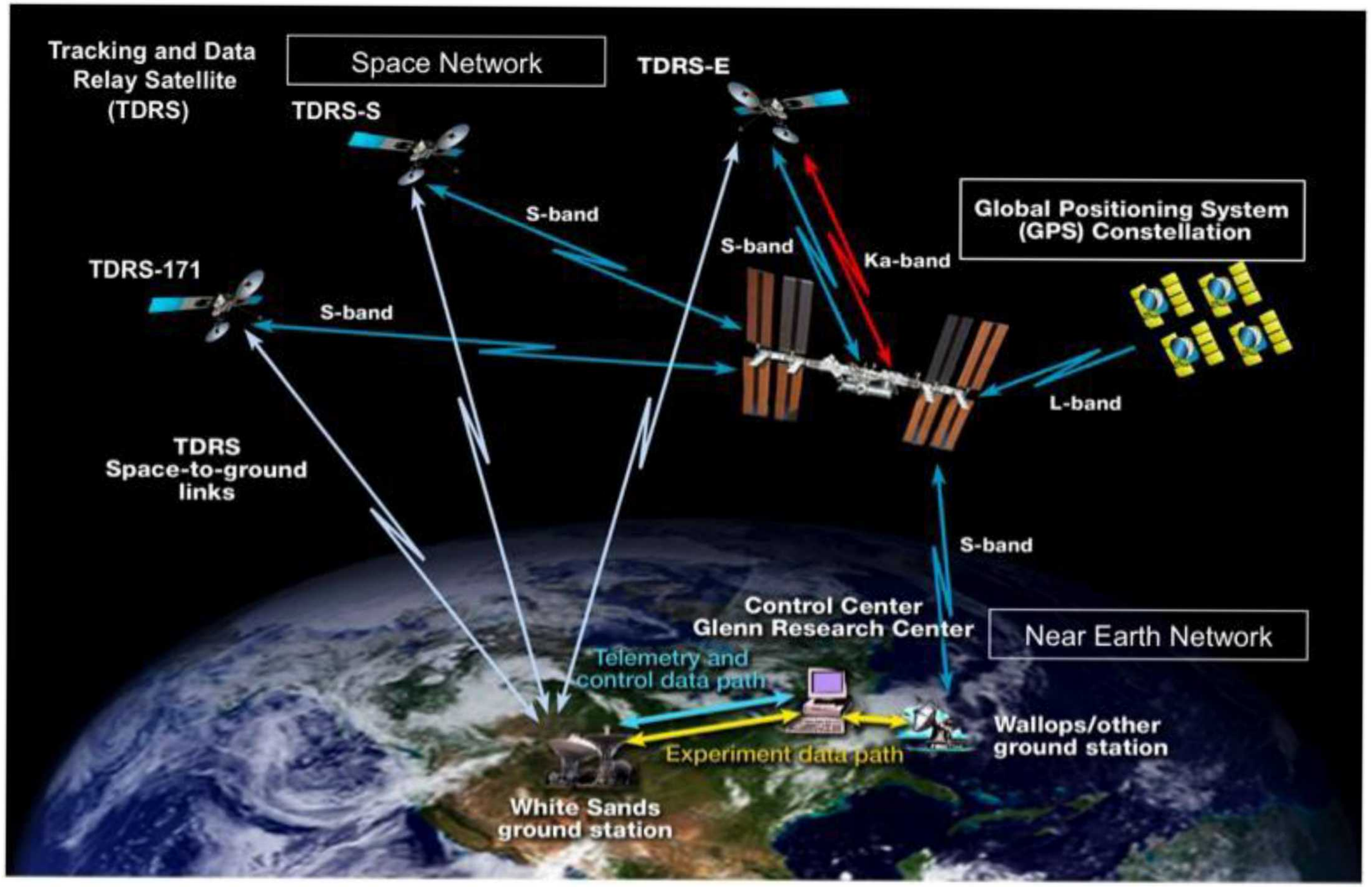
Be agile across all available spectrum

Reinforcement Learning & Game-theoretic Learning

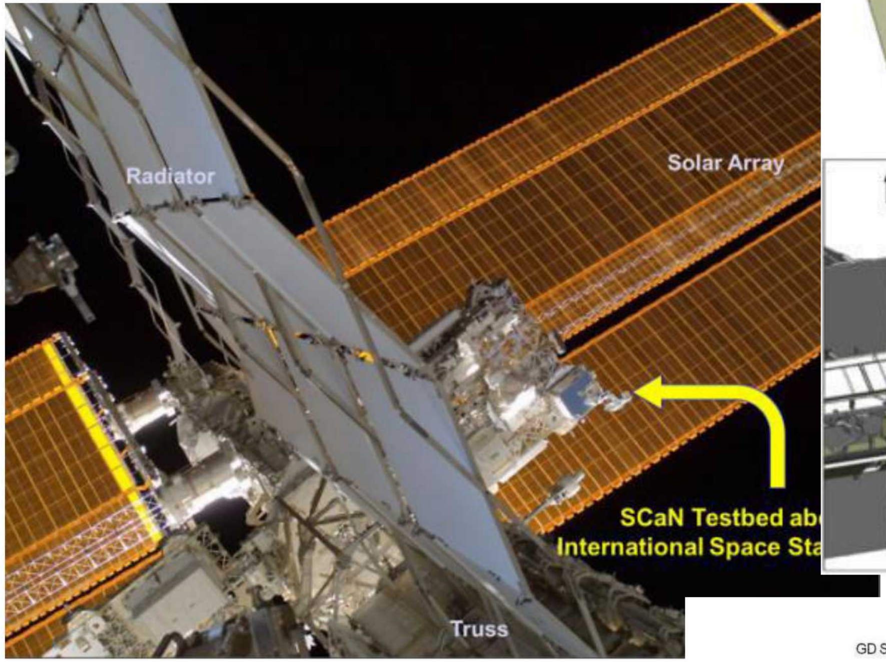
International Space Station (ISS)

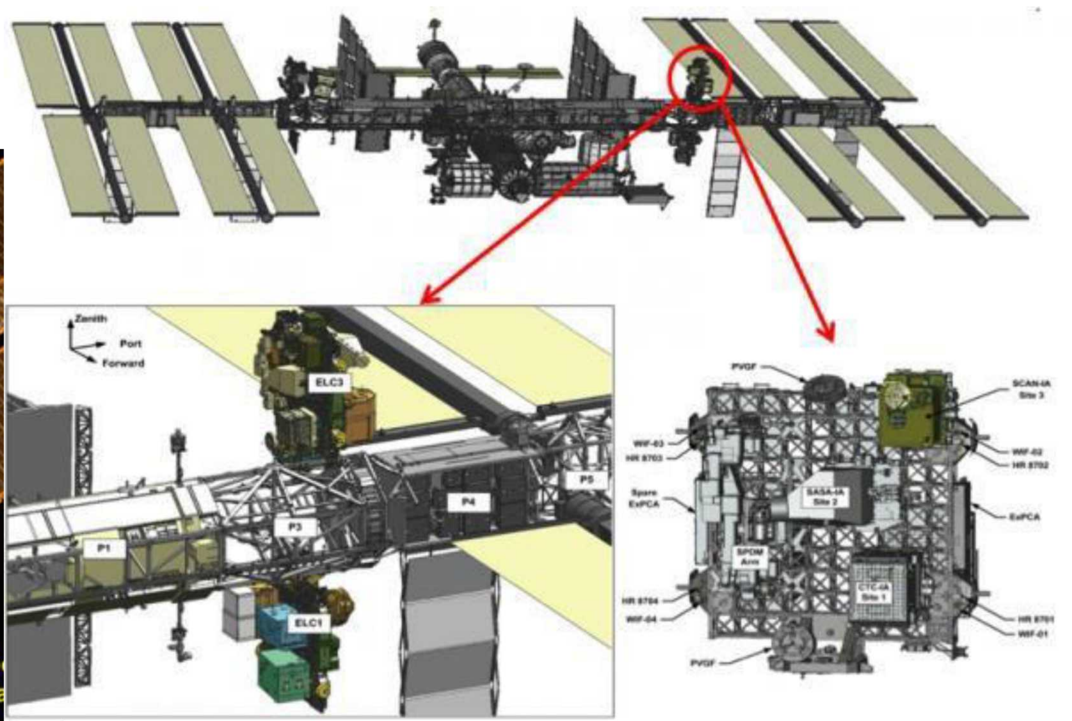


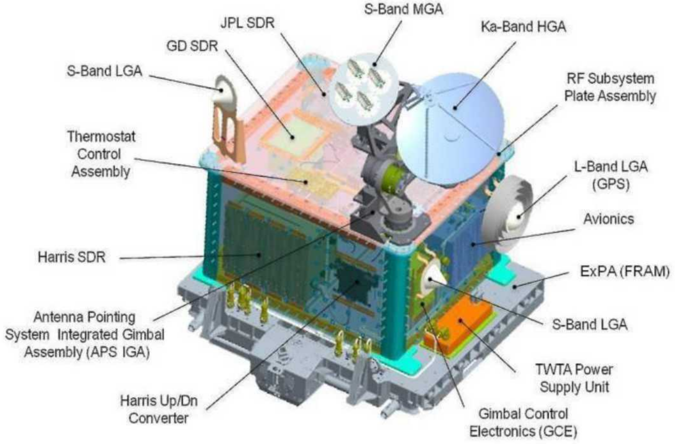
NASA's Space Communications & Navigation (SCaN) Testbed the ISS



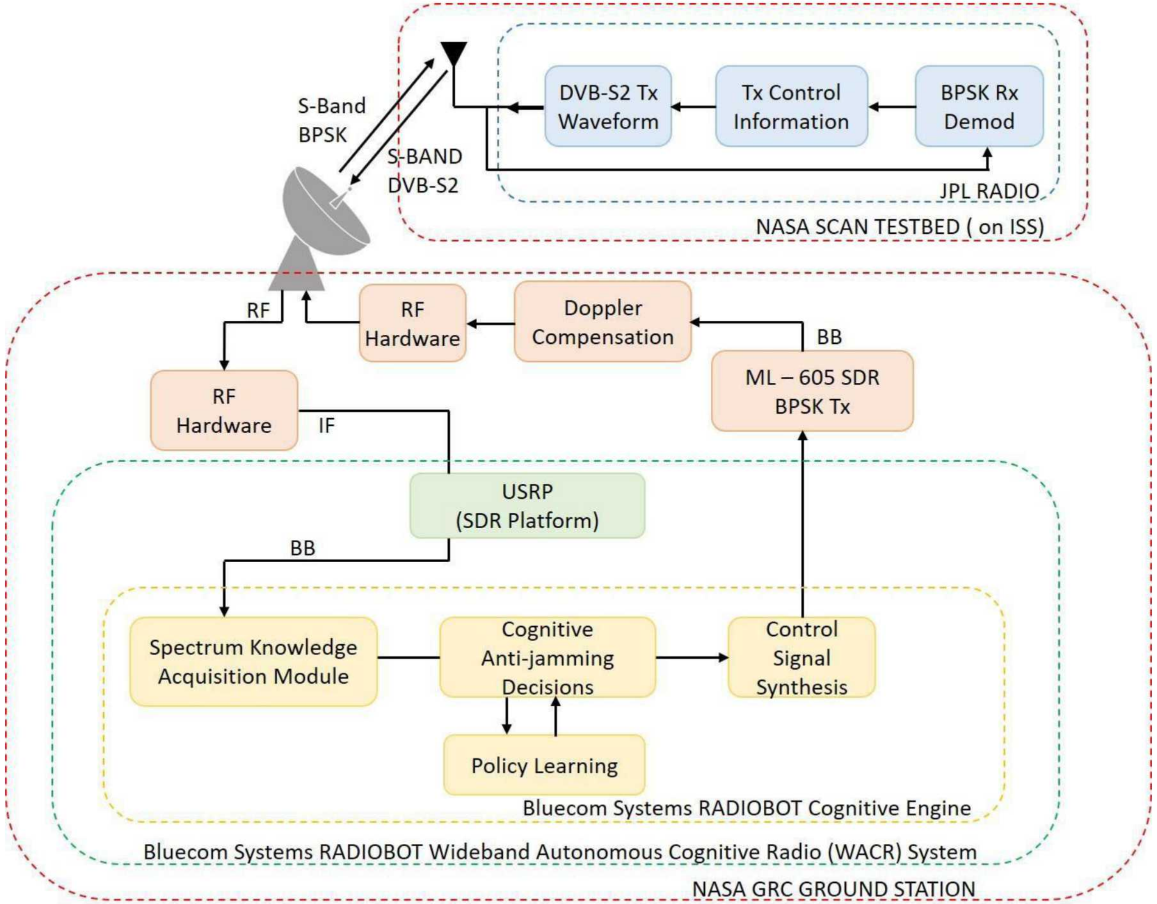
NASA’s (SCaN) Testbed on the ISS





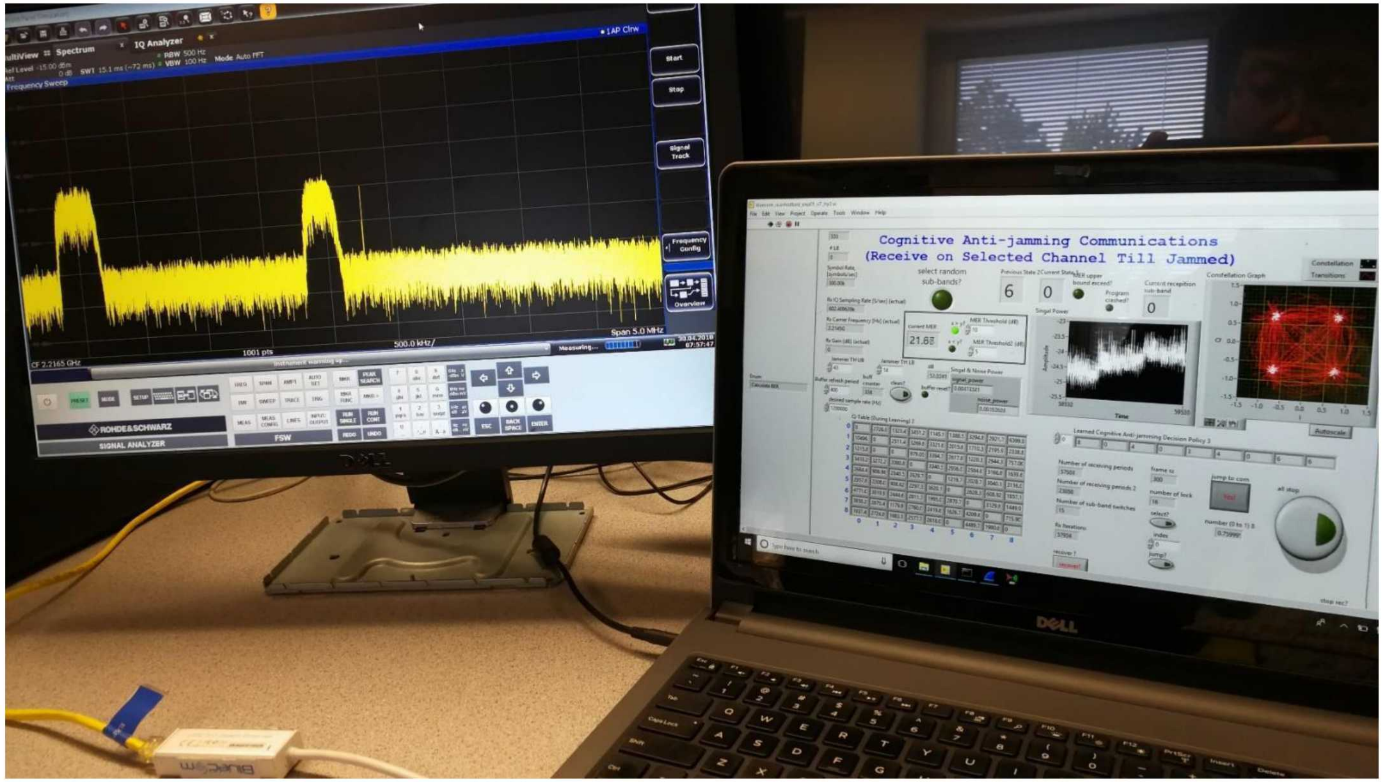


Cognitive Anti-jamming Communications Experiment On SCaN Testbed



S. K. Jayaweera, S. Feng, D. Mortensen, A. Holland, M. Piasecki, M. Evans and C. Christodoulou, "Cognitive Anti-jamming Satellite-to-Ground Communications on NASA's SCaN Testbed", Wireless Innovation Forum Summit on Wireless Communications Technologies (WInnComm), Melbourne, FL, Nov. 2018.

Bluecom/UNM CAJ Exp on SCaN Testbed: Flight Testing (April/May 2018)

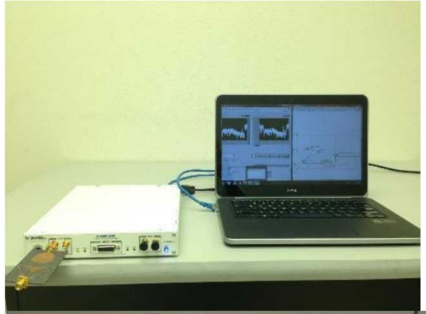


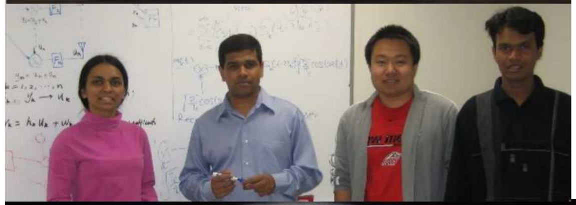
- Demonstrated the first successful cognitive anti-jamming communications on a space/satellite communications network.
  - Radiobot learned and successfully maintained a spectrally agile COM Link!

Communications and Information Science Lab

(CISL)

at ECE@UNM





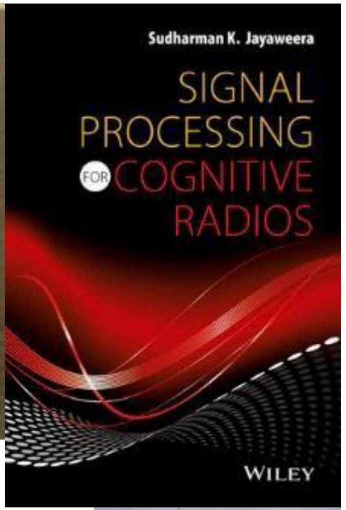
sensor/voice/data/ image

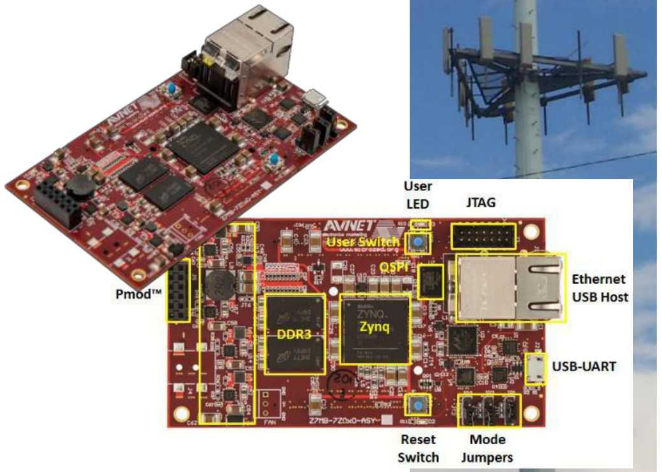
Research in **information**

processing, storing and *transmission.*

Wireless communications

- Cognitive Radios / Cognitive GPS
- Machine / Deep Learning
- RF Spectrum Situational Awareness
- SATCOM
- Space Situational Awareness
- Cyber-physical Systems
- Autonomous Vehicular Networks
- Wireless Communications
- Statistical Signal Processing
- Information Theory
- Networked Control Systems





From Theory to Practice

Wireless, Applied EM, Reconfigurable & Autonomous Systems and Machine Learning R&D for applications in satellite/space and military to emergency and consumer communications.

New Mexico
Research Spotlight Forum

1/29/2019 Artificial Intelligence & Machine Learning

Intelligent Controls for Particle Accelerators and Other Research and Industrial Infrastructures

one application of AI

Sandra G. Biedron, Ph.D.

University of New Mexico and Element Aero

for the intelligent controls team with the major collaborators being

Auralee Edelen, Evelyne Meier, Stephen Milton, Greg LeBlanc†, Jorge Alberto Diaz Cruz

Capability Overview

Sandia National Laboratories

THE UNIVERSITY OF NEW MEXICO

NM STATE UNIVERSITY

NEW MEXICO TECH
SCIENCE • ENGINEERING • RESEARCH UNIVERSITY

SAND2018-14303 O

ABOUT YOURSELF

Brief Biography:

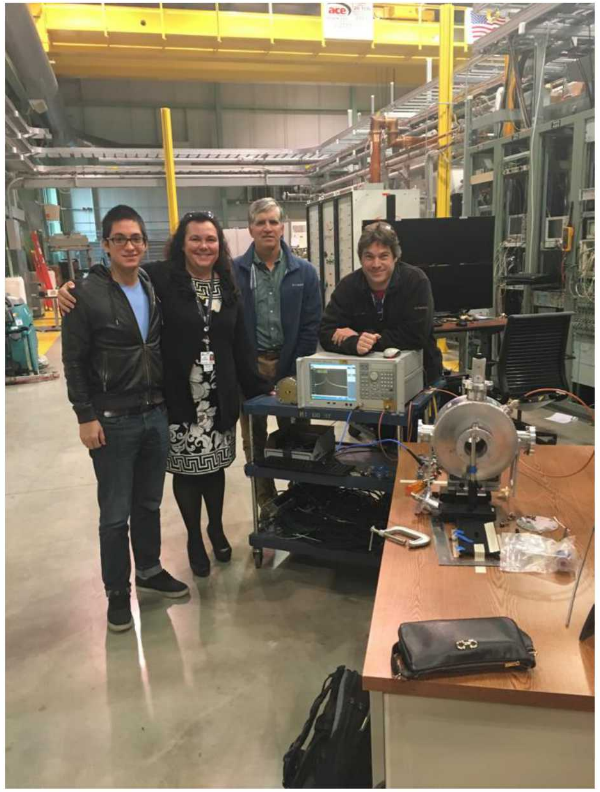
- Sandra G. Biedron is a Research Professor of Electrical and Computer Engineering in the College of Engineering at the University of New Mexico (UNM).
- Since 2002, she has served as the Managing Member of a research and development company Element Aero.
- She holds a Ph.D. in Physics from the Lund University in Sweden.
- She leads many research projects and recently served as Deputy Lead Engineer for the Integration and Test Integrated Product Team of an Innovative Naval Prototype through a Boeing contract. Formerly she was the Department of Defense project office director and a physicist at Argonne National Laboratory and was an associate director of the Argonne Accelerator Institute. Dr. Biedron served as a technical and management consultant on the successful FERMI free-electron laser project at Sincrotrone Trieste (Italy).

- Her interests are many and include particle accelerator systems, laser systems, the use of artificial intelligence in controls, modelling, and prediction of complex systems, sensors and detectors, and applications of these technologies in science, security and defense.

- She is a Fellow of the American Physical Society (APS), a Senior Member of the Optical Society of America (OSA), a Senior Member of the Institute of Electrical and Electronics Engineers (IEEE), a Fellow of the SPIE, and a member of the Italian Optical Society (SIOF).

- In 2010 she was presented a Letter of Commendation by the Chief of Naval Research for her technical efforts and in 2013 she was honored with the George T. Abell Outstanding Mid-Career Faculty Award for the College of Engineering at Colorado State University. In 2018, she received the IEEE Nuclear and Plasma Sciences Society's Particle Accelerator Science and Technology award.

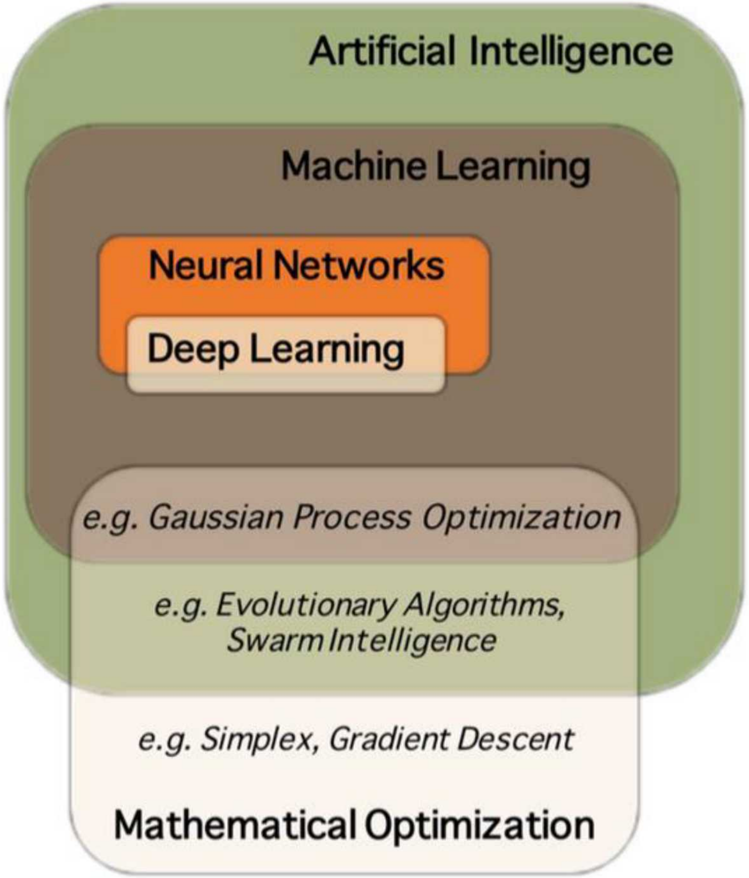
Keywords:
Particle accelerator systems, laser systems, the use of artificial intelligence in controls, modelling, and prediction of complex systems, sensors and detectors, and applications of these technologies in science, security and defense.



PhD student Evelyne Meier (second from right) with (L to R): Edwina Cornish (Monash Deputy Vice Chancellor & Vice President Research), Greg LeBlanc and Sandra Biedron.

What do we mean by "AI and related areas"?

- Artificial Intelligence (AI)
  - *Concerned with enabling machines to exhibit aspects of human intelligence: knowledge, learning, planning, reasoning, perception*
  - Narrow AI: focused on a task or similar set of tasks
  - General AI: human-equivalent or greater performance on any task
- Machine Learning (ML)
  - *Enabling machines to complete tasks without being explicitly programmed*
  - Common tasks: Regression, Classification, Clustering, Dimensionality Reduction
- Neural Networks (NNs)
  - *An approach within ML that uses many connected processing units*
  - Many different architectures and training techniques
- Deep Learning (DL)
  - *Learning hierarchical representations*
  - Right now, largely synonymous with deep (many-layered) NN approaches



Machines as Intelligent Systems
one application of AI

I've been fortunate enough to work on all sorts of controls, including those for laser and particle accelerator systems, general aviation aircraft for security applications, and for a directed energy demonstrator for a weapons system.

Since 2002 I've been interested in intelligent control. Why?

- Simply - We need to make machines or systems better so we needed AI as a tool in *some* cases.
- Since 2004 we have worked to demonstrate intelligent techniques as applied to among other things, particle accelerators.

I will come back to the word ***some*** in a bit.

Machines for physics
Focus on particle accelerators

Particle accelerators are in their own right a branch of science and technology but they are more than that because they enable much research and have many applications.

In the APS there is the Division of the Physics of Beams and in the IEEE Nuclear Plasma Sciences Society there is a Particle Accelerator Science and Technology section.

In support of its science mission, the U.S. Department of Energy operates large scientific instruments that support the work of more than 50,000 scientists worldwide. Large particle accelerators are at the core of eleven of the seventeen National User Facilities that DOE operates.

It is estimated that in the post-1938 era, accelerator science has influenced almost 1/3 of physicists and physics studies and on average contributed to physics Nobel Prize-winning research every 2.9 years*.

We are all cognizant that accelerators have also have led to discoveries also recognized with a prize from other Nobel Prize committees**.

These machines continue to become more complex.

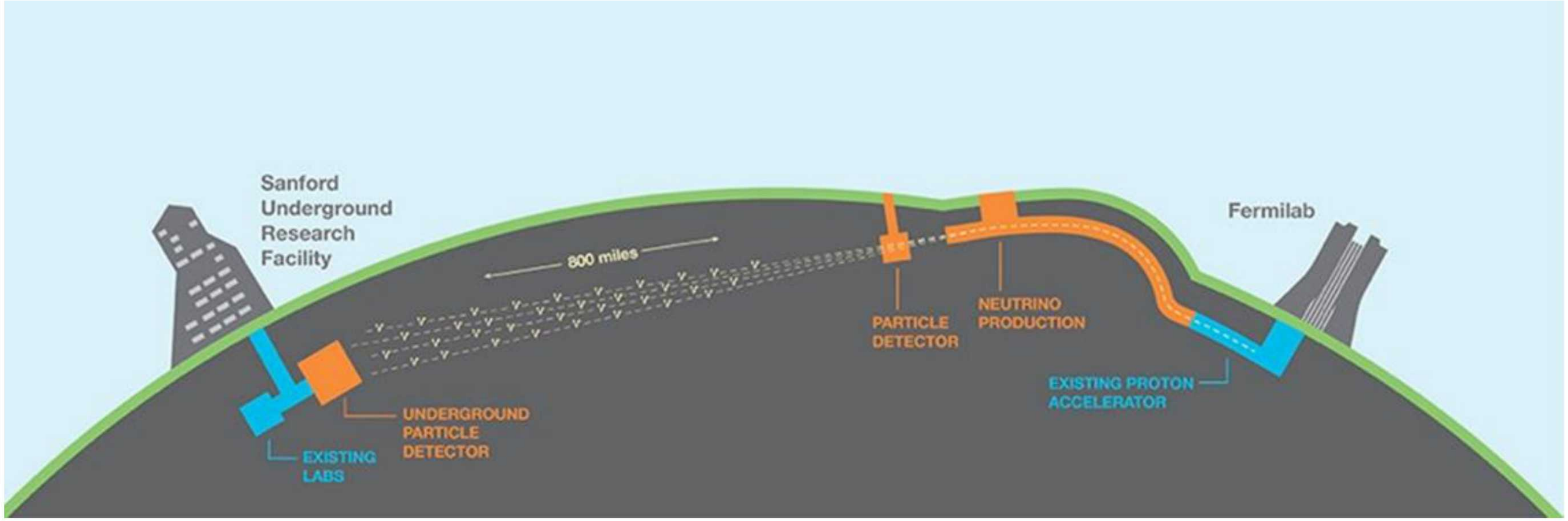
A few examples….

*E.Haussecker, A.Chao, The Influence of Accelerator Science on Physics Research, Physics in Perspective 13 (2011) 146.

**See, for example, Glenn Roberts, "Synchrotrons Play Role in Nobel Prize Research," SLAC Press release 12 October 2012, https://www6.slac.stanford.edu/news/2012-10-12-synchrotron-nobel.aspx.

Example:
Long-Baseline Neutrino Facility/ Deep Underground Neutrino Experiment (LBNF/DUNE)

- A 1.2 MW (2.4 MW phase 2) wide-band neutrino beam
- Detector deep underground (1.5 km) 70kt liquid argon
- A long baseline (1300 km)
- Liquid Argon is next generation neutrino detector technology ….a lot more development needed to perfect



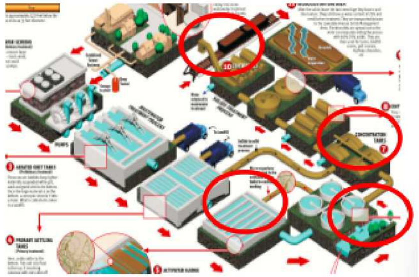
Slide courtesy of
Tim Meyer, Fermilab

Application: Waste Water/Sludge Treatment

- Electron beams create highly reactive species
- Demonstrated effective for:
  - Disinfection of municipal bio-solids
  - Destruction of organics, pharmaceuticals
- Yet, despite demonstrations ~no market penetration

Accelerator above is 3 stories tall!

- Why? Municipalities are conservative; don't finance R&D
  - High power, cost effective, industrial accelerators have not been available to deploy* e.g. * http://science.energy.gov/~/media/hep/pdf/accelerator-rd-stewardship/Energy_Environment_Report_Final.pdf
  - Compact SRF accelerators can change this situation
- IARC is partnered with the Chicago Metropolitan Water Reclamation District (MWRD)
  - Operate largest treatment plant in the world
  - Identified multiple areas to evaluate EB
  - Bio-solids, cell lysis, destroy pharmaceuticals



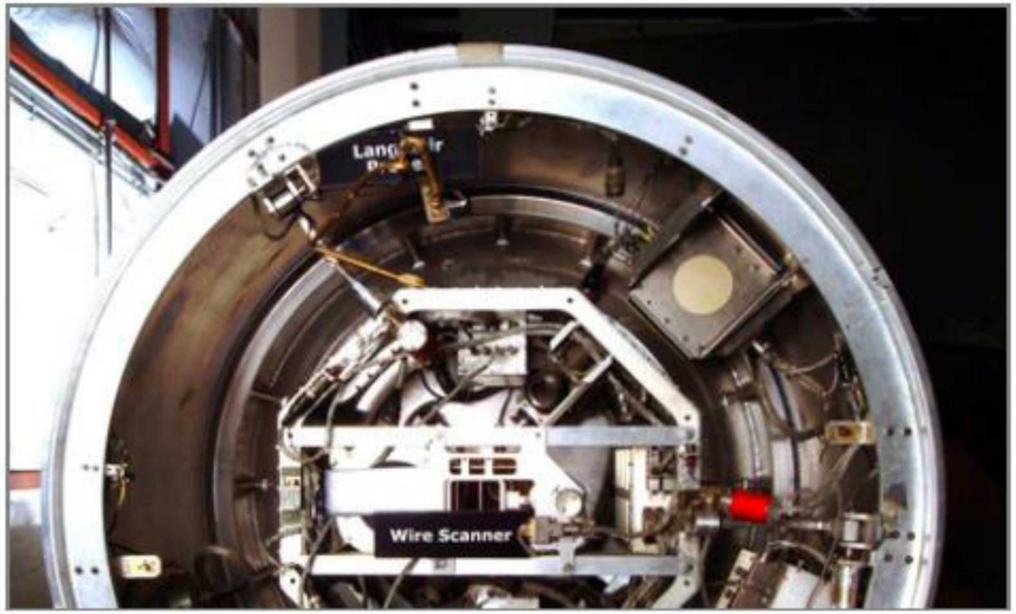
Fermilab

17 R. Kephart TUIA2, IPAC17, Copenhagen Denmark 5/16/2017

See for example, R. Kephart, B. Chase, I. Gonin, A. Grassellino, S. Kazakov, T. Khabiboulline, S. Nagaitsev, R. Pasquinelli, S. Posen, O. Pronitchev, A. Romanenko, V. Yakovlev (Fermi National Accelerator Laboratory), S. Biedron, S. Milton, N. Sipahi (Colorado State University), and S. Chattopadhyay and P. Piot (Northern Illinois University), 2015, “SRF, Compact Accelerators for Industry & Society,” In: Proceedings of SRF2015, www.JACoW.org, paper FRBA03, 1467-1473.

Example
Security and defense

March 2018 - **"Directed energy is more than just big lasers," said Michael Griffin Undersecretary for Defense for Science and Engineering. "That's important. High-powered microwave approaches can affect an electronics kill. The same with the neutral particle beam systems we explored briefly in the 1990s"** for use in space-based anti-missile systems. Such weapons can be "useful in a variety of environments" and have the "advantage of being non-attributable," meaning that it can be hard to pin an attack with a particle weapon on any particular culprit since it leaves no evidence behind of who or even what did the damage.



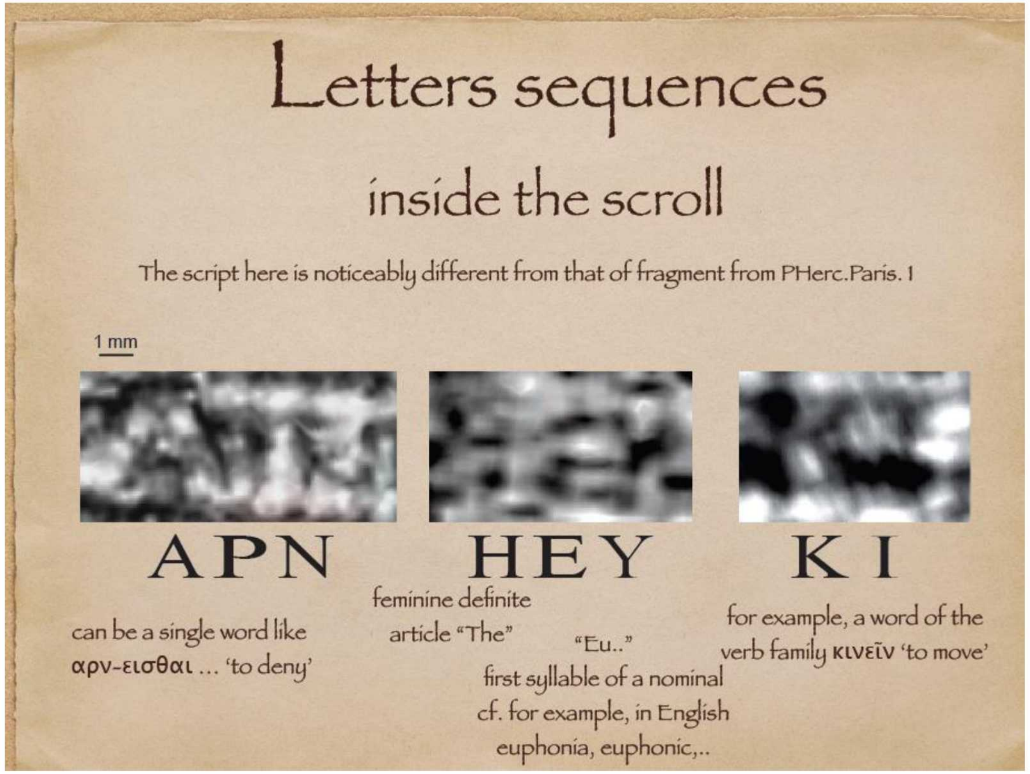
As part of the Beam Experiments Aboard Rocket project, this neutral particle beam accelerator was launched from White Sands in July 1989 to an altitude of 200 kilometers (124 miles), operated successfully in space in July, 1989. National Air and Space Museum Collection

Example

Enabling reading of what otherwise is lost.

Revealing letters in rolled Herculaneum papyri by X-ray phase-contrast imaging

Nature Communications volume 6, Article number: 5895 (2015)



Slide courtesy of Vito Mocella

And the examples continue…

- Medicine (cancer treatment and radio-isotope production)
- Security
- Industrial Processing
- etc…

Particle Accelerators

Technical challenges that can be found on such devices

- A big player in the research infrastructure budget
  - Recall just in the U.S. - "Large particle accelerators are at the core of eleven of the seventeen National User Facilities that DOE operates."
- This means we want them to operate in the state we want for all the scheduled operational hours.
  - We want to reduce the time needed to bring system to its operational state.
  - We want to keep the system in its operational state for as long as we define it.
  - We want to continue to develop components and better for more sustained, improved operation for the scientific machines. The same can be said for accelerators in medicine, industry, security…

Particle Accelerators
Technical challenges that can be found on such devices that scream for AI

- Many parameters to monitor and control in various sub-systems
- Interacting sub-systems
- On-demand changes in operational states
- Many small, compounding errors
- Complex/non-linear dynamics
- Machine model does not equal as-built so challenges from day 1.
- Time-varying/non-stationary behavior
- Diagnostics also limited because of cost, space, inability to physically characterize at all locations OR when existent not put to full use in control (e.g. images)
- Problems that do not have an algorithmic solution or where the solution is very complex
- etc.

Particle Accelerators
How smarter techniques began to be explored

- These sometimes unstable, jittery, uncertain, time-varying, non-linear, ever-increasing parameter systems that might need to be semi-autonomous looked pretty prime for "intervention" for optimization and intelligent control investigations. Oh, did I mention sometimes aging, re-purposed equipment can come into play too?
- So since 2004, we plugged along at this for FEL applications and began publishing in 2009. But – as with anything new, as mentioned in the APS News (June 2018, "AI Makes Inroads in Physics") there have been many naysayers.
- In part because a few attempts in the 1990s in this field did not work optimally.
- Now, things have advanced in several areas better enabling this research and applications.

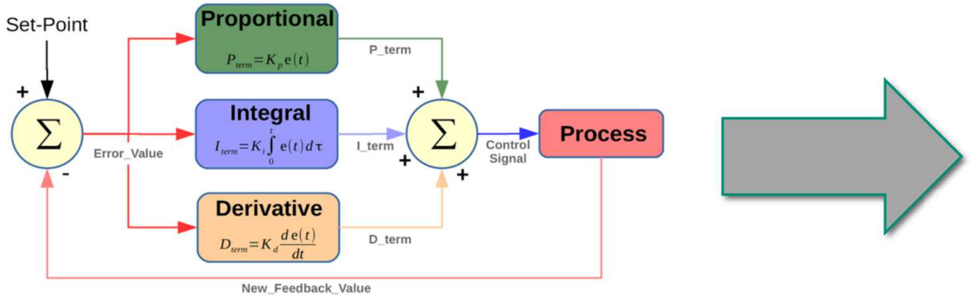
Particle Accelerators
Operator-run facilities

- We need things done that the operators, including scientists and engineers do
  - Optimization
  - Planning
  - Diagnostics analysis
  - Model learning
  - Prediction
  - Learning control

Courtesy of Advanced Photon Source, Argonne National Laboratory

What have we* explored?

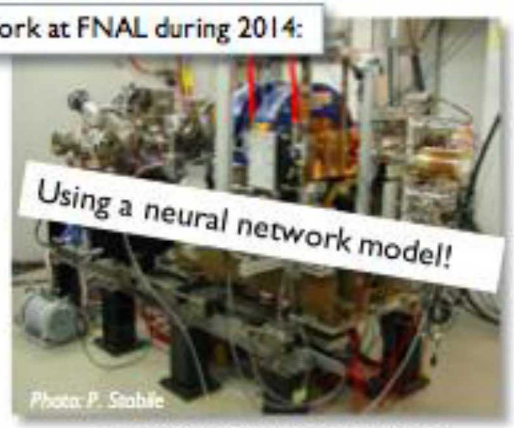
- Learned neural network models (from simulation or measurements) to speed up computational time and increase accuracy to real systems. The models can be updated with additional measured/collected data. Have found better than codes/models based on first principles only.
- Model Predictive Control (Prediction + Planning)
- Model and Policy Learning
- Image Processing



*In the interest of time and space, I am limiting the examples here to what we have explored. I will list the associated workshops that have covered related activities in the appendix as additional references.

A. Edelen likes to point out

Work at FNAL during 2014:

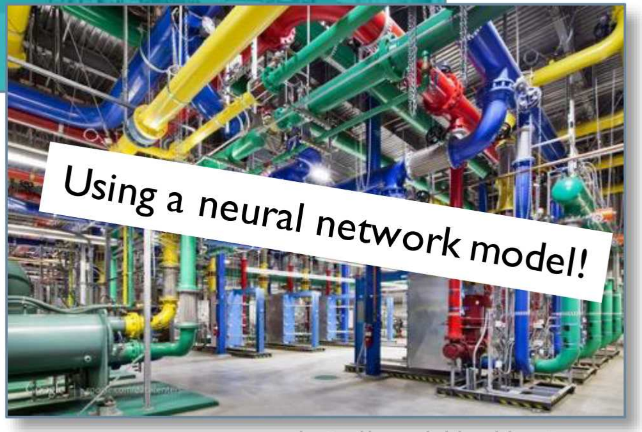


A. L. Edelen, et al. IPAC15, TUPOA51

Global News in 2016:

DeepMind AI Reduces Google Data Centre Cooling Bill by 40%

Transport delays, variable heat load
Efficient servers alone not enough



https://googleblog.blogspot.com

A.L. Edelen, S.G. Biedron, B.E. Chase, D. Edstrom, S.V. Milton, P. Stabile, 2016, “Neural Networks for Modeling and Control of Particle Accelerators,” IEEE Transactions on Nuclear Science 63(2), 878-897. (Invited paper)

Closing thoughts

- Research and work ongoing in the intelligent control, modeling and prediction of infrastructures such as particle accelerators.
- A new grant from the DOE Accelerator Stewardship Program will help link the ongoing research to several end-users of accelerators.
- We are happy to lend our expertise if needed.
- See related workshops, list of some publications, and information on the IEEE efforts in AI in the next charts.

Some publications and recent workshops

List of recent workshops

- Intelligent Controls For Particle Accelerators 30-31 Jan 2018 Daresbury Laboratory - www.cockcroft.ac.uk/events/ICPA/
- ICFA Beam Dynamics Mini-Workshop: Machine Learning Applications for Particle Accelerators conf.slac.stanford.edu/icfa-ml-2018/
- American Physical Society's - Physics Next: Machine Learning October 8-10, 2018 - https://journals.aps.org/physics-next/2018/machine-learning

-E. Meier, S.G. Biedron, G. LeBlanc, M.J. Morgan, 2011, "Development of a Novel Optimization Tool for Electron Linacs Inspired by Artificial Intelligence Techniques in Video Games," Nuclear Instruments and Methods in Physics Research Section A 632, 1-6.

- E. Meier, S.G. Biedron, et al. , 2009, "Electron Beam Energy and Bunch Length Feed Forward Control Studies Using an Artificial Neural Network at the Linac Coherent Light Source," Nuclear Instruments and Methods in Physics Research Section A 610, 629-635.

- E. Meier, M. Morgan, S.G. Biedron, G. LeBlanc, J. Wu, 2009, "Development of a Combined Feed Forward-Feedback System for an Electron Linac," Nuclear Instruments and Methods in Physics Research Section A 609, 79-88.

- E. Meier, S.G. Biedron, G. LeBlanc, M.J. Morgan, 2010, "Artificial Intelligence Systems for Electron Beam Parameters Optimisation at the Australian Synchrotron," In: Proceedings of the 2010 International Particle Accelerator Conference, www.JACoW.org, paper TUPEC025, 1770-1772.

- E. Meier, S.G. Biedron, G. LeBlanc, M.J. Morgan, J. Wu, 2009, "Electron Beam Energy Stabilization Using a Neural Network Hybrid Controller at the Australian Synchrotron Linac," In: Proceedings of the 2009 Particle Accelerator Conference, www.JACoW.org, paper TU5RFP050, 1201-1203.

- E. Meier, S.G. Biedron, G. LeBlanc, M.J. Morgan, J. Wu, 2009, "Electron Beam Energy Stabilisation Test Results Using a Neural Network Hybrid Controller at the Australian Synchrotron and LINAC Coherent Light Source Projects," In: Proceedings of the 2009 Free Electron Laser Conference, 766-771.

- A. Morin, S.G. Biedron, S.V. Milton, et al , 2014, "Trajectory Response Studies at the Thomas Jefferson National Accelerator Facility Energy Recovery Linac and Free Electron Laser," In: Proceedings of the Sixteenth Annual Directed Energy Symposium, 10-14 March 2014, Huntsville, Alabama, Directed Energy Professional Society.

- A. Morin, C. Tennant, S. Biedron, D. Douglas, S. Milton, 2012, "Control Systems Development for the Thomas Jefferson National Accelerator Facility Free Electron Laser: Preliminary Results for Trajectory Response Data," In: Proceedings of the Fifteenth Annual Directed Energy Symposium, 26-30 November 2012, Albuquerque, New Mexico,. Directed Energy Professional Society.

- S.G. Biedron, A.L. Edelen, S.V. Milton, "Advanced controls for light sources," in Advances in Laboratory-based X-Ray Sources, Optics, and Applications V, Ali M. Khounsary, Gert E. van Dorssen (eds.), Proc. SPIE 996404(2016).

- A.L. Edelen, S.G. Biedron, B.E. Chase, D. Edstrom, S.V. Milton, P. Stabile, 2016, "Neural Networks for Modeling and Control of Particle Accelerators," IEEE Transactions on Nuclear Science 63(2), 878-897. (Invited paper)

- J.P. Edelen, D. Bowring, B.E. Chase, and J. Steimel (FNAL), A.L. Edelen, S.G. Biedron, and S.V. Milton (CSU), 2017, "First Principles Modeling of RFQ Cooling Systems and Resonant Frequency Responses for Fermilab's PIP-II Injector Test," IEEE Transactions on Nuclear Science, vol. 64, no.2, pp. 800-808.

- A. Edelen, S. Biedron, J.P. Edelen, S.V. Milton, P.J.M van der Slot, "Using A Neural Network Control Policy For FEL Tuning: An Exploratory Simulation Study With a THz FEL," Proceedings of the 2017 Free-Electron Laser Conference, to be published. (JACOW).

- A. Edelen, S. Biedron, S. Milton, D. Bowring, B.E. Chase, J. Edelen, J. Steimel, "Resonant Frequncy Control fo the PIP-II Injector Test," In: Proceedings of NA-PAC2016, MOPOB17.

- A. Edelen, S. Biedron, "First Steps Toward Incoprorating Image Based Diagnostics into Particle Accelerator Control Systems Using Convolutional Neural Networks," In: Proceedings of NA-PAC2016, TUPOA51.

- D. Bowring, B. Chase, J. Czajkowski, J. Edelen, D. Nicklaus, J. Steimel, T. Zuchnik, Fermilab, A. Edelen, S. Biedron, S. Milton, 2016, "Resonance Control for Fermlab's PXIE RFQ," In: Proceedings of the 2016 International Particle Accelerator Conference, www.JACoW.org, paper MOPMW026, 447-450.

- A.L. Edelen, S.G. Biedron, S.V. Milton, D. Bowring, B.E. Chase, J.P. Edelen, J. Steimel, 2016, "Neural Network Model of the PXIE RFQ Cooling System and Resonant Frequency Response," In: Proceedings of the 2016 International Particle Accelerator Conference, www.JACoW.org, paper MOPWI028, 4131-4133.

- S. Biedron, A. Edelen, S. Milton, 2016, "Advanced Controls for RF and Directed Energy Systems - This Ain't Your Father's Control System," In: Proceedings of the Directed Energy Professional Society's Annual Directed Energy Symposium, 7-11 March 2016, Albuquerque, New Mexico.

- S. Biedron, A. Edelen, and S. Milton, 2016, "Advanced Controls for Accelerators," In: High-Brightness Sources and Light-Driven Interactions, Proceedings of the Compact (EUV & X-ray) Light Sources Conference, OSA technical Digest (online), Optical Society of America, paper EM9A.3.

- A.L. Edelen, S.G. Biedron, S.V. Milton, B.E. Chase, D.J. Crawford, N. Eddy, D. Edstrom Jr., E.R. Harms, J. Ruan, J.K. Santucci, P. Stabile, 2015, "Initial Experimental Results of a Machine Learning-Based Temperature Control System for an RF Gun," In: Proceedings of the 2015 International Particle Accelerator Conference, www.JACoW.org, paper MOPWI028, 1217-1219.

Switching gears a bit

Appendix with charts from the IEEE

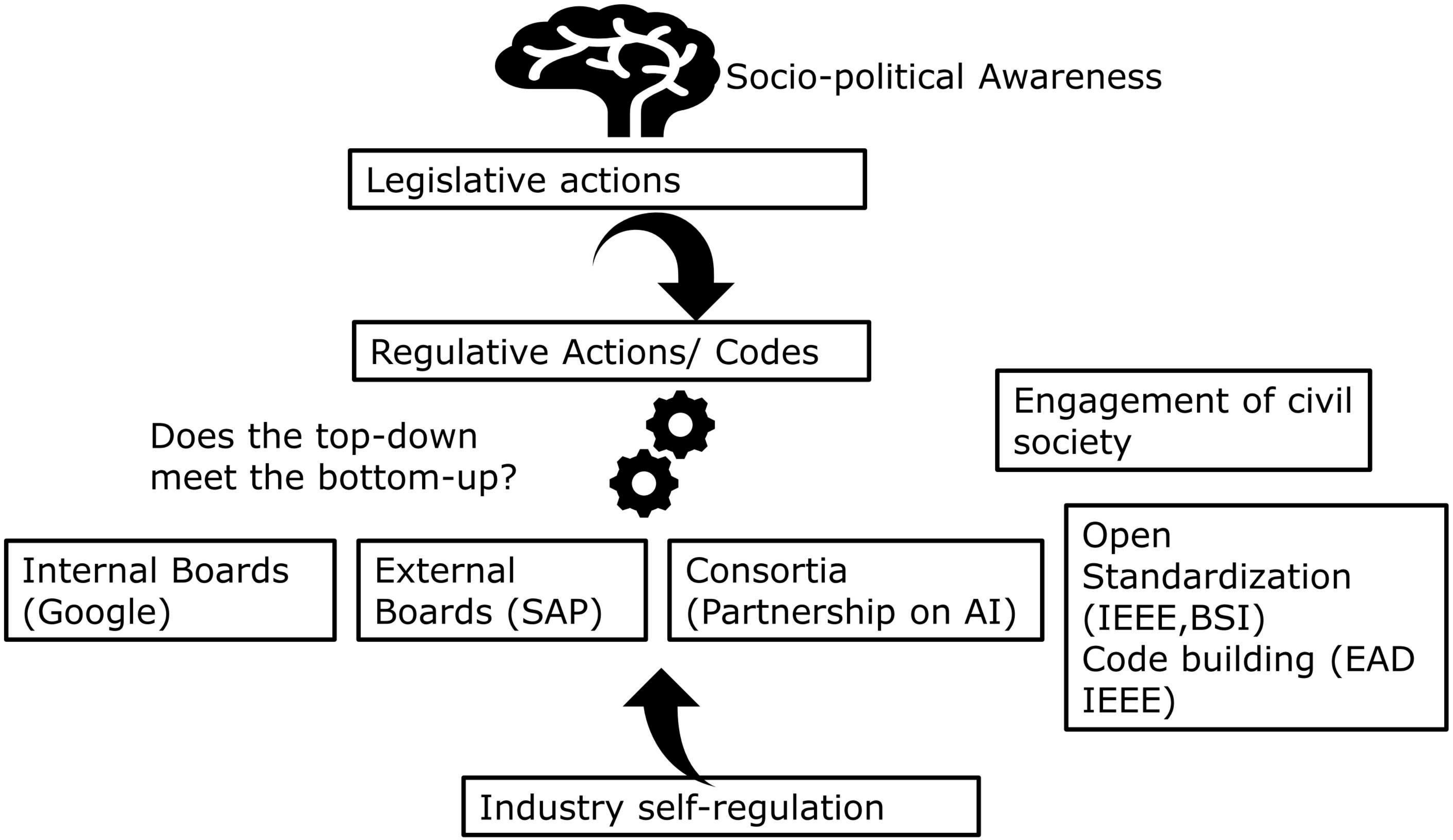
Stressing *some* systems

- I'm preaching to the choir here a bit but I wanted to stress the word *some*.
- Some of us have been at using AI for a long time and are cognizant of where AI is actually needed/useful and when it is responsible to use.

- Despite the rush to incorporate artificial intelligence (AI) into every component of our lives, the truth is, not all systems (or sub-systems) require intelligent controls for reliable operation or for their interpretation.
- As the old saying goes – "Just because you can [build it/use it] doesn't mean you should."
- Some complex systems, however, can greatly benefit from the responsible and well-architected incorporation of control techniques with intelligent characteristics, in some cases that intelligent component encompassing the technique of machine learning.

Charts courtesy of IEEE

Working together toward a human-centric AI?



Lots of people suggest “AI Principles”

- Several lists, some original, some “cut and paste” from others
- Reflecting various interests and agendas (industry lobbies, activist NGOs, proxy-religions, existential fears, etc.)
- Confusing categorization, mixing of political, cultural and technical levels
- Partly overlapping, even conflicting aspects

➢ For this OECD group to have a chance to succeed, we will need to establish rather fast a conceptual framework to address the categorization problem.

➢ A possibility to conceptualize at a higher level such principles could be to follow the categorization implicit in slide 2 of Ms Doaa "Multi-disciplinary approaches to Ethical AI"

From “interdisciplinary approaches” to “principles categories” ?

- Philosophical Approaches → *Values principles/aspirational intentions*

  Which societal, moral, cultural, political values do we **intend** to promote through intelligent systems?
  Self-determination, political autonomy/democracy, dignity, privacy, social fairness,….

- Legal Approaches → *Legal principles/obligations*

  Which current or emerging legal frameworks **must** we take into account?
  Human rights, children rights, personal data protection, liability laws, ...

- Computational Approaches → *Systems design principles/ technical implementations*
  \-
  Are the systems **dependable**, ie are they doing what they are supposed to do?
  How to measure and verify?
  The 3 principles on Slide 5 of Ms Doaa fall under this category.

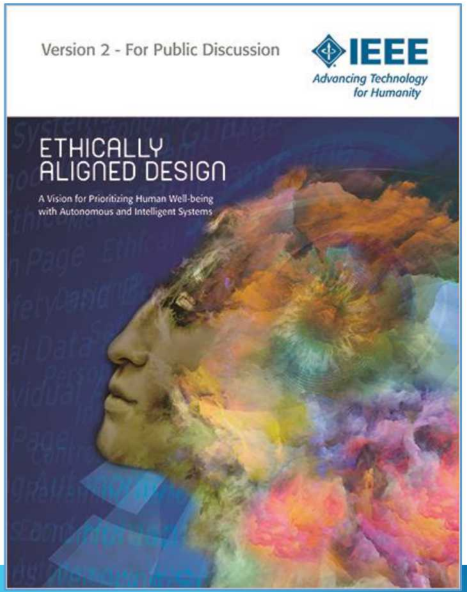
IEEE’s Path toward a human-centric AI

- Established in 2016 the **IEEE Global Initiative on Ethics of Autonomous and Intelligent Systems**
- It is an open, global and inclusive (regionally, culturally, gender etc.) community of experts and interested persons from technology and human science to address this question
- Within two years, a community of ~ 1500 people from all continents, ~ 40 % women
- Its mission is to **ensure that every stakeholder involved in the design and development of autonomous and intelligent systems is educated, trained, and empowered to prioritize ethical considerations so that these technologies are advanced for the benefit of humanity**
  - There seems to be a great affinity between this and OECD’s mission regarding a human-centric AI.

Other adjacent IEEE (SA) Initiatives:
Global Council on Extended Intelligence
Open Community for Ethics in Autonomous and Intelligent Systems (OCEANIS)

Works of the IEEE Global Initiative on Ethics of Autonomous and Intelligent Systems

- **Ethically Aligned Design**
  An iterative process over 3 years with open and massive participation toward a better understanding of the fundamental issues, combined with a process for suggesting high-level principles and actions to address them. No corporate or geopolitical or activists agendas seem to dominate the process.
  Crowd-sourced, collective, unbiased intelligence at its best
  - EAD V1 (2016) and V2 (2017) received 100s of pages of public feedback
  - Currently, 13+ Committees are creating content for V3 (early 2019)
  - **The most comprehensive, crowd-sourced global treatise regarding the ethics of Autonomous and Intelligent Systems available today**
  - Provides an open platform for thought leadership and action to prioritize values-driven, ethically-aligned design for autonomous and intelligent systems.



- **P7000 series of standardization projects**
  Where we believe that - beyond suggesting high-level principles - we may become more concrete and achieve consensus in a meaningful time frame.

- **Education material/curricula**
  Establishment of EAD University Consortium (in 2019).

Global Council on Extended Intelligence

- IEEE-SA and the MIT Media Lab announced the launch of the global Council on Extended Intelligence (CXI) on 22 June 2018
- The goals of CXI are to build a new narrative for autonomous and intelligent technologies inspired by principles of systems dynamics and design.
- CXI will promote the deals of responsible participant design, data agency and metrics of economic wellbeing prioritizing people and planet over exponential growth, including these projects:
  - **Extended Intelligence - Awareness and Action –** will focus on creating an introduction to Extended Intelligence and Participatory Design
  - **Digital Identity - Democracy by Design –** will focus on creation of Data Policy template for governments and organizations to utilize in helping individuals and society reclaim their digital identity in the algorithmic age
  - **Enlightened Indicators - Measuring What's Good Versus Simply Growth –** will focus on creating a Wellbeing Indicator template, a metric governments and organizations can utilize in genuinely measuring prosperity in terms of benefit to all

Open Community for Ethics in Autonomous and Intelligent Systems (OCEANIS)

- IEEE-SA jointly launched and became a founding member on 25 July 2018
- OCEANIS is a high level global forum for discussion, debate and collaboration among organizations interested in the development and use and development of standards in autonomous and intelligent systems.
- Community will address needs for coordination and collaboration related to the unprecedented challenges faced by those working in ICT standards and related spaces.
- OCEANIS is open to all interested organizations.
  In addition to IEEE-SA, Founding Members include the:

-African Regional Organization for Standardisation (ARSO)
-Austrian Electrotechnical Association (OVE)
-Austrian Standards International (A.S.I.)
-British Standards Institution (BSI)
-China Electronic Standardizations Institute (CESI)
-CIO Strategy Council (Canada)
-International Electrotechnical Commission (IEC)
-Ecuadorian Service for Standardization (INEN)
-National Standards Authority of Ireland (NSAI)
-Turkish Standards Institute (TSE)
-Verband und Deutsche Kommission Elektrotechnik Elektronik Informationstechnik

IEEE Initiatives & activities around autonomous/intelligent systems:

<table>
<tr><th>Standards</th><th>Other Activities</th></tr>
<tr><td rowspan="3">IEEE 7000 Series Standards:
• 7000 - Model Process for Addressing Ethical Concerns During System Design
• 7001 - Transparency of Autonomous Systems
• 7002 - Data Privacy Process
• 7003 - Algorithmic Bias Considerations
• 7004 - Standard for Child and Student Data Governance
• 7005 - Standard for Transparent Employer Data Governance
• 7006 - Standard for Personal Data Artificial Intelligence (AI) Agent
• 7007 - Ontological Standard for Ethically Driven Robotics and Automation Systems
• 7008 - Standard for Ethically Driven Nudging for Robotic, Intelligent and Autonomous Systems
• 7009 - Standard for Fail-Safe Design of Autonomous and Semi-Autonomous Systems
• 7010 - Wellbeing Metrics Standard for Ethical Artificial Intelligence and Autonomous Systems
• 7011 - Standard for the Process of Identifying and Rating the Trustworthiness of News Sources
• 7012 - Standard for Machine Readable Personal Privacy Terms
• 7013 - Inclusion and Application Standards for Automated Facial Analysis Technology</td><td>Industry Connection Group:
• The IEEE Global Initiative on Ethics of Autonomous and Intelligent Systems
• Launch of the NeuroTech Industry Connections Group</td></tr>
<tr><td>IEEE Brain Initiative Workshop on Advanced NeuroTechnologies</td></tr>
<tr><td>IEEE Brain Sensors Workshop</td></tr>
</table>

Other related IEEE Activities

Journals-examples

- IEEE Transactions on Neural Networks and Learning Systems
- IEEE Intelligent Systems
- IEEE Transactions on Fuzzy Systems
- IEEE Transactions on Nuclear Science
- IEEE Transactions on Human-Machine Systems
- IEEE Transactions on Cybernetics
- EEE Transactions on Control Systems Technology
- IEEE Transactions on Automation Science and Engineering
- IEEE Transactions on Industrial Informatics
- IEEE Transactions on Systems, Man, and Cybernetics: Systems
- IEEE Transactions on Circuits and Systems
- IEEE Transactions on Pattern Analysis and Machine Intelligence
- IEEE Transactions on Cognitive and Developmental Systems
- IEEE Transactions on Image Processing
- IEEE Robotics and Automation Letters
- IEEE Transactions on Emerging Topics in Computational Intelligence

Other related IEEE Activities

Journals- special issues- examples
• Computer – Sept 2018 – The future of AI • IEEE JSAC (Journal on Special areas in Communications) Special Issue on Artificial Intelligence and Machine Learning for Networking and Communications • IEEE Transactions on Engineering Management - Special Issue: Services Computing Management for Artificial Intelligence and Machine Learning • IEEE Transactions on Network Science and Engineering-Special Issue on Big Data and Artificial Intelligence for Network Technologies • Journal of Biomedical and Health Informatics – Special issue -Pervasive Sensing and Machine Learning for Mental Health • IEEE Internet of Things Journal - RRCPS: Reliable and Resilient Cyber-Physical Systems

Other related IEEE Activities

Artificial Intelligence (34)-conferences

- 2018 International Conference on Advanced Computation and Telecommunication (ICACAT), 28 Dec - 29 Dec 2018
- 2018 IEEE International Conference on Artificial Intelligence and Virtual Reality (AIVR), 10 Dec - 12 Dec 2018
- 2018 3rd International Conference on Pattern Analysis and Intelligent Systems (PAIS), 24 Oct - 25 Oct 2018
- 2018 IEEE 3rd Advanced Information Technology, Electronic and Automation Control Conference (IAEAC), 12 Oct - 14 Oct 2018
- 2018 First International Conference on Secure Cyber Computing and Communication (ICSCCC), 11 Oct - 13 Oct 2018
- 2018 IEEE International Conference on Systems, Man, and Cybernetics (SMC), 07 Oct - 10 Oct 2018
- 2018 First International Conference on Artificial Intelligence for Industries (AI4I), 26 Sep - 28 Sep 2018
- 2018 Joint IEEE 8th International Conference on Development and Learning and Epigenetic Robotics (ICDL-EpiRob), 17 Sep - 20 Sep 2018
- 2018 Intelligent Systems Conference (IntelliSys), 06 Sep - 07 Sep 2018
- 2018 IEEE International Conference on Autonomic Computing (ICAC), 03 Sep - 07 Sep 2018
- 2018 IEEE Conference on Computational Intelligence and Games (CIG), 14 Aug - 17 Aug 2018
- 2018 International Conference on Computer and Applications (ICCA), 06 Aug - 07 Aug 2018
- 2018 IEEE International Work Conference on Bioinspired Intelligence (IWOBI), 18 Jul - 20 Jul 2018
- 2018 33rd Annual ACM/IEEE Symposium on Logic in Computer Science (LICS), 09 Jul - 12 Jul 2018
- 2018 10th International Conference on Modelling, Identification and Control (ICMIC), 02 Jul - 04 Jul 2018
- 2018 10th International Conference on Electronics, Computers and Artificial Intelligence (ECAI), 28 Jun - 30 Jun 2018
- 2018 19th IEEE/ACIS International Conference on Software Engineering, Artificial Intelligence, Networking and Parallel/Distributed Computing (SNPD), 27 Jun - 29 Jun 2018
- 2018 IEEE International Conference on Smart Computing (SMARTCOMP), 18 Jun - 20 Jun 2018
- 2018 Second International Conference on Intelligent Computing and Control Systems (ICICCS), 14 Jun - 15 Jun 2018
- 2018 Global Internet of Things Summit (GIoTS), 04 Jun - 07 Jun 2018

Other related IEEE Activities

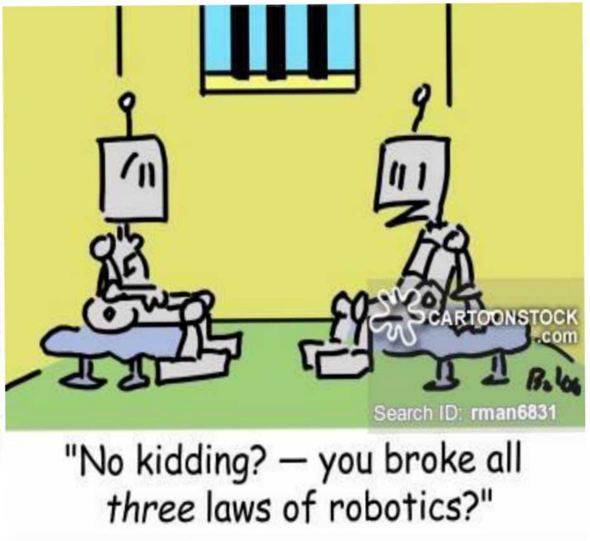
Artificial Intelligence (34)-conferences

- 2018 International Conference on Optical Network Design and Modeling (ONDM), 14 May - 17 May 2018
- 2018 International Symposium on Consumer Technologies (ISCT), 11 May - 12 May 2018
- 2018 9th International Conference on Information and Communication Systems (ICICS), 03 Apr - 05 Apr 2018
- 2018 International Conference on Control, Automation and Diagnosis (ICCAD), 19 Mar - 21 Mar 2018
- 2018 13th ACM/IEEE International Conference on Human-Robot Interaction (HRI), 05 Mar - 08 Mar 2018
- 2018 International Conference on Intelligent Autonomous Systems (ICoIAS), 01 Mar - 03 Mar 2018
- 2018 International Conference on Emerging Technologies in Data Mining and Information Security (IEMIS), 23 Feb - 25 Feb 2018
- 2018 Second International Conference on Computing Methodologies and Communication (ICCMC), 15 Feb - 16 Feb 2018
- 2018 International Conference on Communication information and Computing Technology (ICCICT), 02 Feb - 03 Feb 2018
- 2018 International Conference on High Performance Computing in Asia-Pacific Region (HPC Asia), 29 Jan - 31 Jan 2018
- 2018 IEEE International Conference on Future IoT Technologies (Future IoT), 18 Jan - 19 Jan 2018
- 2018 10th International Conference on Agents and Artificial Intelligence (ICAART), 16 Jan - 18 Jan 2018
- 2018 IEEE International Conference on Big Data and Smart Computing (BigComp), 15 Jan - 17 Jan 2018
- 2018 8th International Conference on Cloud Computing, Data Science & Engineering (Confluence), 11 Jan - 12 Jan 2018

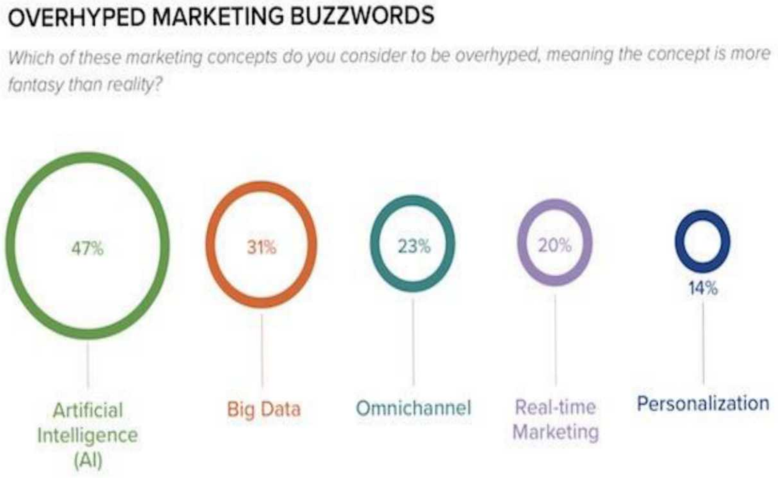
What not to do

Resist to dogmata

Do not oversimplify



Don't confuse science with marketing



Contacts at the IEEE for the EAD

Alpesh Shah alpesh.shah@ieee.org

Sam Sciacca s.sciacca@ieee.org

New Mexico Research Spotlight Forum

1/29/2019 Artificial Intelligence & Machine Learning

Research in the Machine Learning Group, ECE, UNM

Manel Martinez-Ramon, Electrical and Computer Engineering Department, The University of New Mexico

manel@unm.edu

Capability Overview

Sandia National Laboratories | THE UNIVERSITY OF NEW MEXICO | NM STATE UNIVERSITY | NEW MEXICO TECH SCIENCE • ENGINEERING • RESEARCH UNIVERSITY

ABOUT MYSELF

Manel Martínez-Ramón, professor. King Felipe VI Endowed Chair

- PhD, 1999, Telecommunications Engineer, 1996
- Associate professor in different Spanish Universities (2003-2013)
- Professor, ECE, UNM (2013-present)
- Research in Machine Learning and applications
- Research group: 7 PhD (4 post proposal), 4 MsD
  - 2 PhD and 1 MsD from Spain
  - 3 PhD and 2 MsD students form India
  - 1 PhD from Nepal
  - 1 Phd and 1 MsD students from New Mexico
  - Group interests: Cyber Human Systems, Cognitive radio, Smart Grid

Keywords:

Kernels, Multi-task Gaussian Processes, Deep Learning, Anomaly detection, Electric power forecast, Situational awareness, Communications

CURRENT WORK IN ARTIFICIAL INTELLIGENCE/ MACHINE LEARNING

Smart Grid: Load and generation forecast.

- Grid stability.
- Anomaly detection.

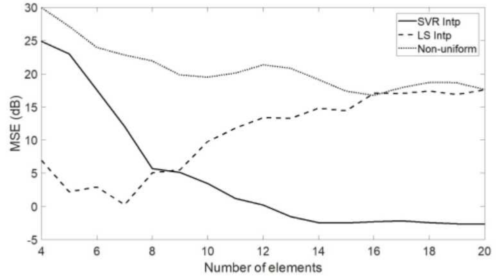
Communications:

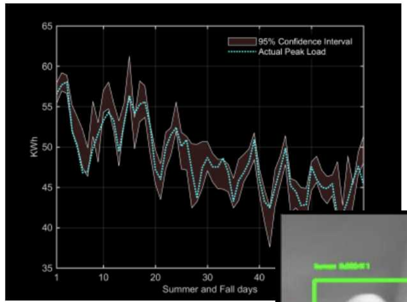
- Forecast of communications resources.
- Radio signal classification.
- Random array beamforming

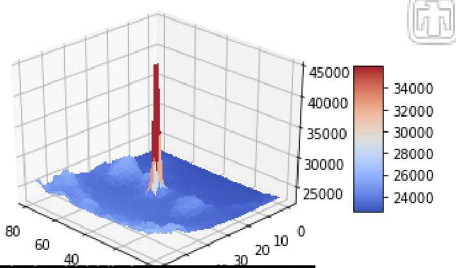
Cyber Human systems for first responders:

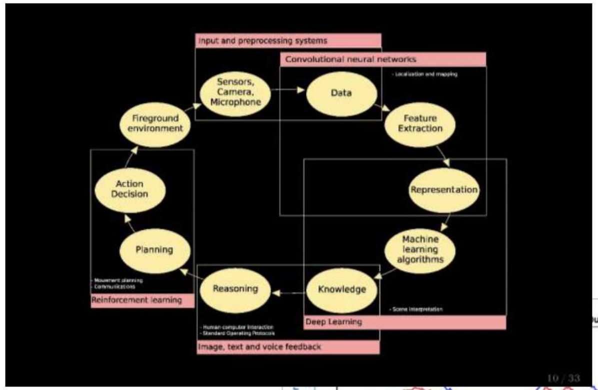
- Thermal Imaging detection: humans (poses, emotions), objects (ladders, windows, doors)
- Fire and smoke detection and characterization.
- Search and rescue.
- Non invasive physiological measurements.

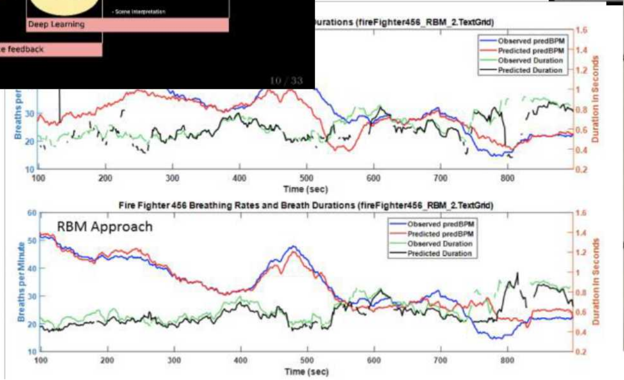
- Probabilistic machine learning theory

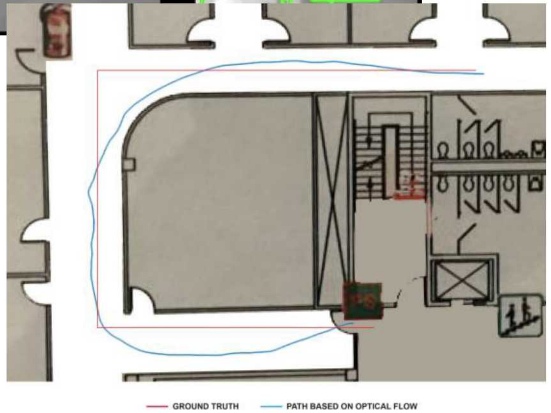


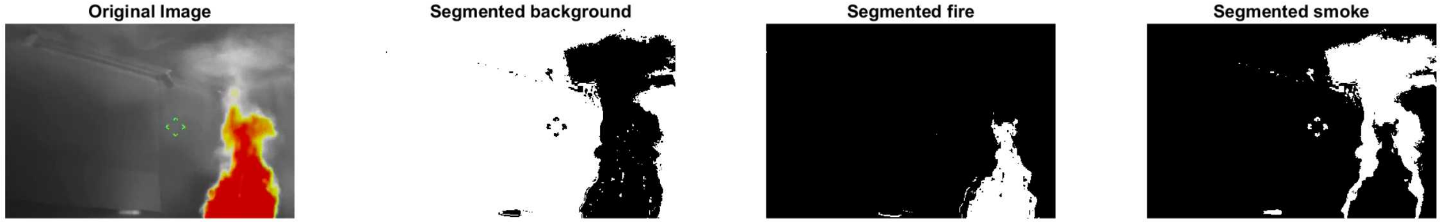












FUNDING SOURCES

- National Science Foundation: Next Generation Smart and Connected Fire Fighter System.
  - Collaboration with National Fire Protection Association
- National Science Foundation: EPSCOR SMART Grid Center
  - Collaboration with NMSU, NMTECH, others
- New Mexico Public School Facility Authority
- Pending: EMERA, Ideas-Tek, Bluecom

RESEARCH NEEDS

Machine learning for new or hot topic applications, for example:

- Security.
- Non supervised fault, anomaly, intrusion detection and characterization.
- Situational awareness in
  - Cyber human systems (first responders safety, security, privacy guaranteed monitoring of persons with disabilities),
  - Smart Grid (fault detection, curtailment minimization, EV, green source penetration…),
- Meters and sensors that are really smart: what to sense, what to transmit, and when.
- Communications: smart antenna coordinated comms., resource efficiency, tactical devices,

Data and knowledge sharing is fundamental for

- Progress in research.
- Discovery of new research needs.
- Grant proposal success.

New Mexico
Research Spotlight Forum

1/29/2019 Artificial Intelligence & Machine Learning

Falls Risk Classification Using Smartphone Based Inertial Sensors and Deep Learning

Phillip DeLeon, New Mexico State Univ., Klipsch School of Electrical and Computer Eng., pdeleon@nmsu.edu
http://wordpress.nmsu.edu/pdeleon/

Matthew Martinez, Sandia National Laboratories, Statistical Sciences, mtmart@sandia.gov

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Capability Overview

Sandia National Laboratories | THE UNIVERSITY OF NEW MEXICO | NM STATE UNIVERSITY | NEW MEXICO TECH SCIENCE • ENGINEERING • RESEARCH UNIVERSITY

ABOUT US

Phillip De Leon

- Professor, Electrical & Computer Eng and Associate Dean of Research
- Time-frequency signal analysis, Speech processing, Machine Learning

Keywords:

Time-frequency signal analysis, empirical mode decomposition(EMD), falls risk prediction, speaker verification (anti-spoofing)

Matthew Martinez

- Statistical Sciences (9136)

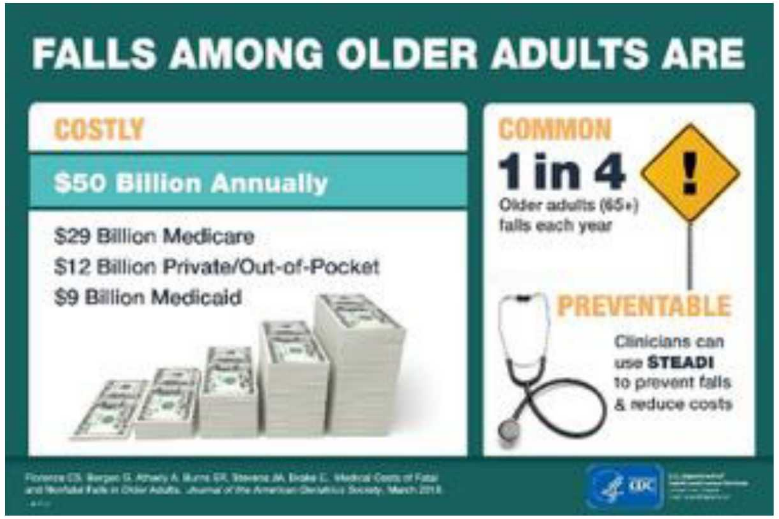
Keywords:

Digital Signal Processing, Deep Learning and Machine Learning for Time Series Analysis, Uncertainty Analysis, Monte Carlo Simulation

FALLS PREVENTION / FALLS RISK RESEARCH BACKGROUND

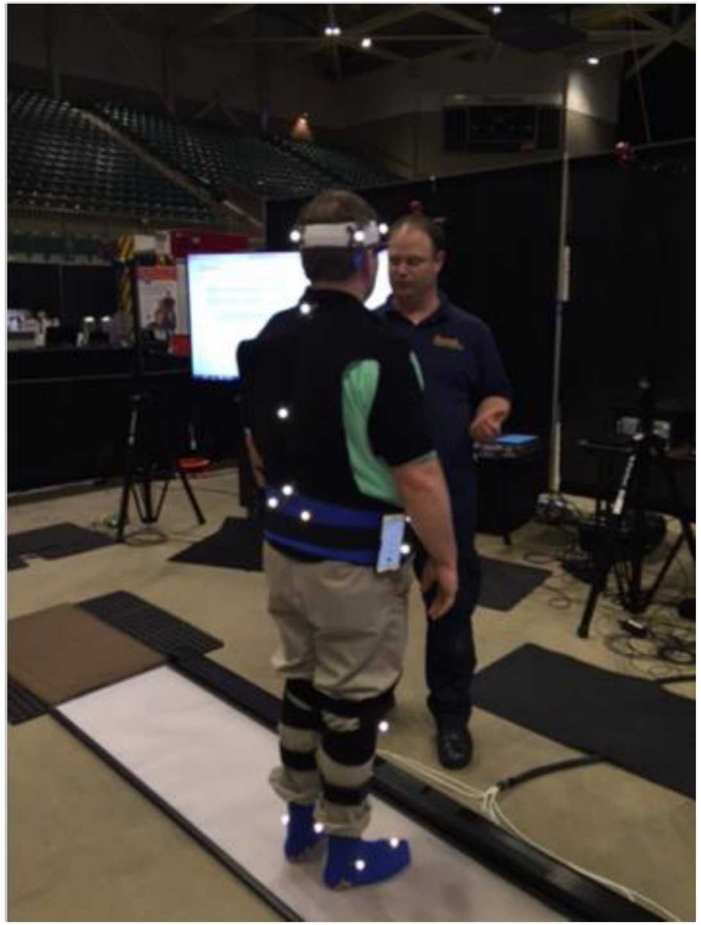
- Each year 2.8 million adults are treated for fall related injuries
  - Broken bones, hip fractures, traumatic brain injury
  - Results in 800,000 hospitalization each year
- Falls Prevention Research
  - Research has focused on assessment, prevention, and rehabilitation
  - Qualitative- and mobility-based assessments
  - Prior research has shown certain gait factors indicate elevated risk of falling
- Sensors for Gait Analysis
  - 3-D motion capture, Pressure sensitive walkways, inertial sensors
  - Inertial Sensors allow for continuous gait monitoring

Our research seeks to use smartphone-based inertial measurements and deep learning to classify older adults as either low or high falls risk



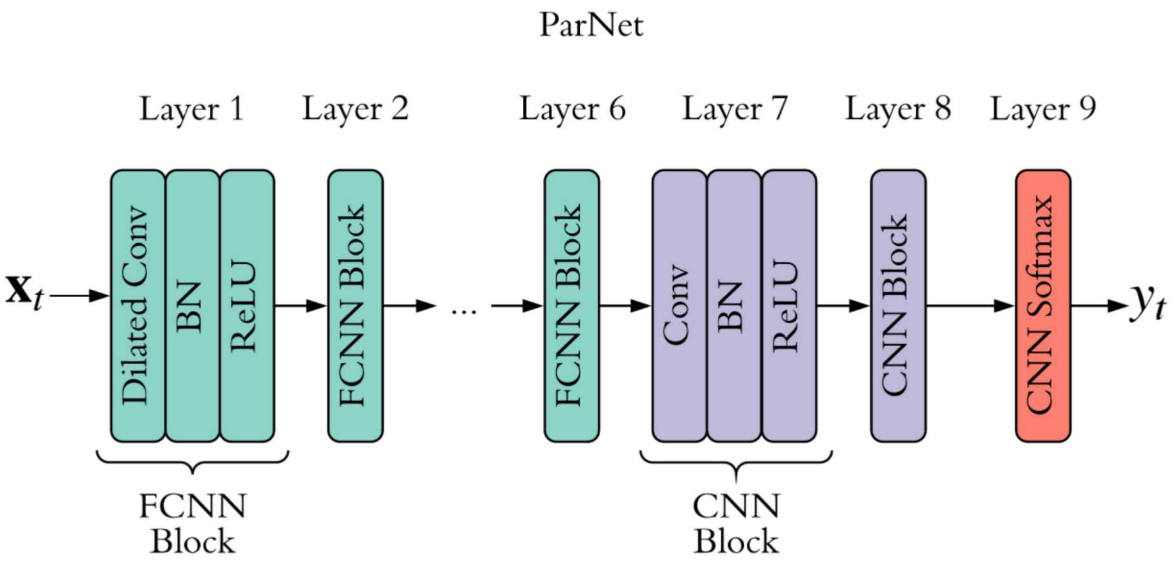
DATA SETS, LABELING, AND TRANSFER LEARNING

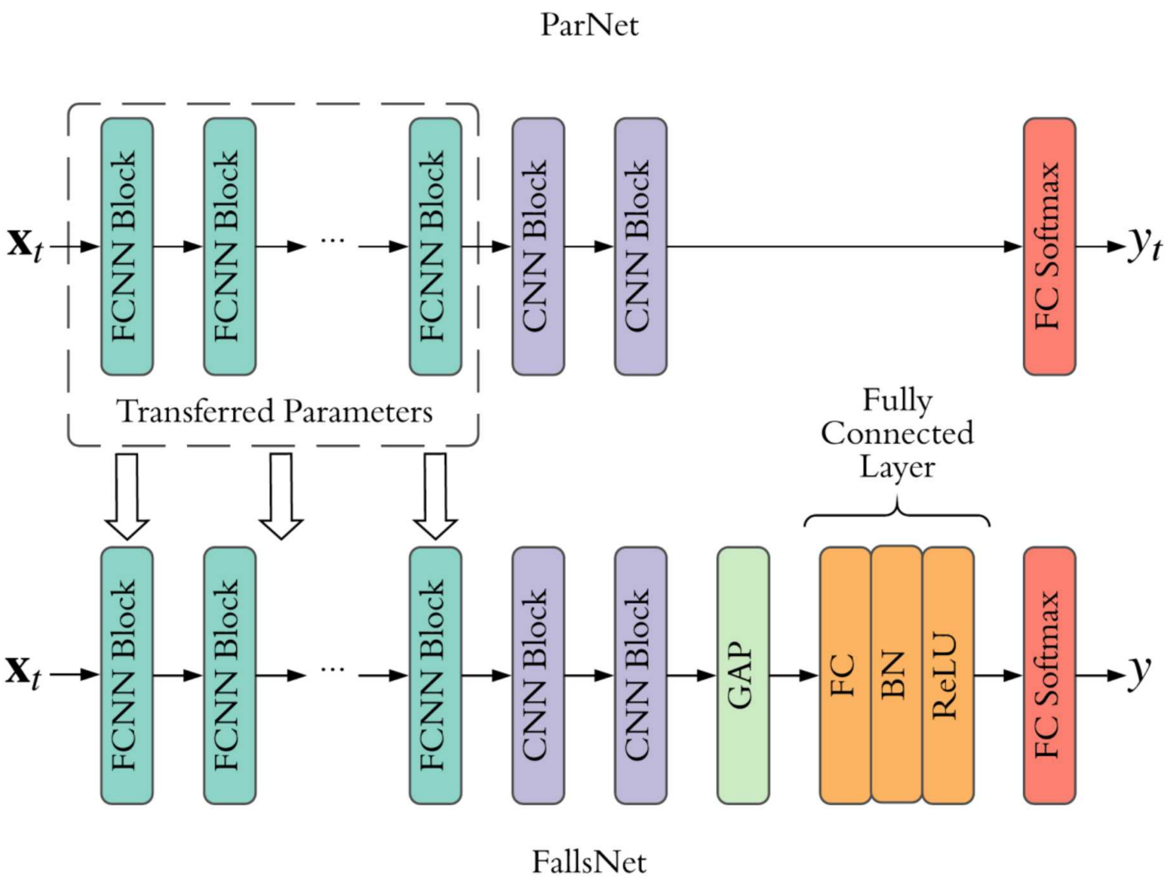
- Parallel data sets (IMU+Walkway)
  - Data collected in partnership with the Electronic Caregiver Company
  - Inertial data (3-axis acceleration and 3-axis gyroscope) collected with (2) Apple iPhone 6 smartphones using custom data logger app
  - Biomechanical data collected from pressure sensitive walkway
  - Data collected 256 participants age 65+
- We used biomechanical measurements from walkway data to label IMU data as low risk/high falls risk based
- Dataset is too small for adequate training of DNN
  - Train DNN for Pedestrian Activity Recognition task using HASC-PAC2016
  - Apply transfer learning to ParNet to adapt for falls risk classification task FallsNet



[1] J. Verghese, R. Holtzer, R. B. Lipton, and C. Wang, "Quantitative gait markers and incident fall risk in older adults," *J. Gerontol. A Biol. Sci. Med. Sci.*, vol. 64A, no. 8, pp. 896–901, Aug. 2009.
[2] M. Martinez, P. L. De Leon, and D. Keeley, "Bayesian Classification of Falls Risk", *Gait & Posture*, vol. 67, pp. 99-103, Jan. 2019.

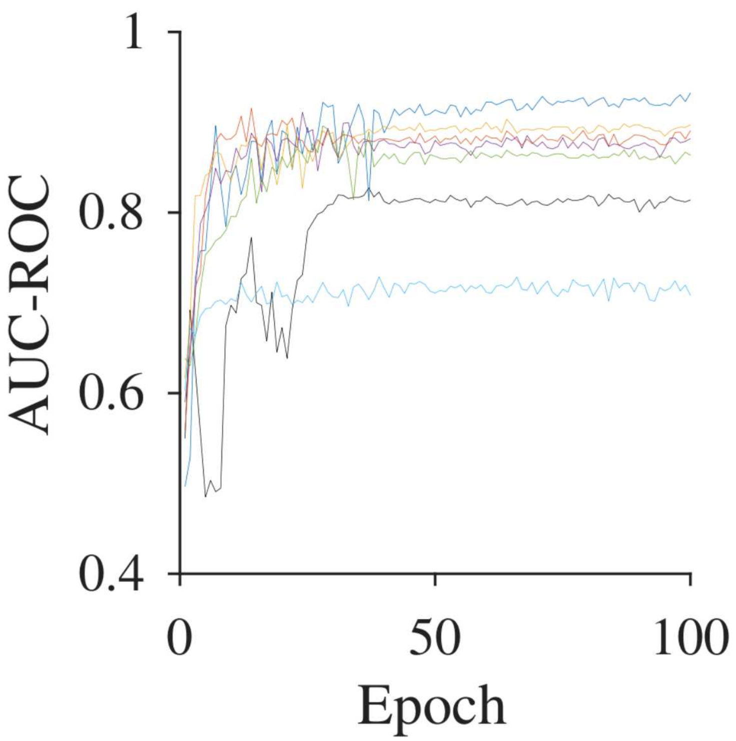
DEEP NEURAL NETWORK ARCHITECTURE FOR FALLS RISK PREDICTION





[3] M. Martinez and P. L. De Leon, "Falls Risk Classification of Older Adults Using Deep Neural Networks and Transfer Learning," in review *IEEE J. Biomed. Health Inform.*, Jan. 2019.

RESULTS WITH TRANSFER LEARNING



Model	Layers Transferred, l, to FallsNet					
	1	2	3	4	5	6
ParNet(All, Accel)	92.1	89.7	90.4	89.7	87.0	**81.3**
ParNet(All, Accel + Gyro)	92.1	91.7	91.5	90.1	87.9	71.9
ParNet(Waist, Accel)	91.3	91.2	**92.1**	88.8	**89.7**	79.2
ParNet(Waist, Accel + Gyro)	**93.3**	**91.5**	90.3	**91.1**	86.9	73.5

[3] M. Martinez and P. L. De Leon, "Falls Risk Classification of Older Adults Using Deep Neural Networks and Transfer Learning," in review *IEEE J. Biomed. Health Inform.*, Jan. 2019.

CONCLUSIONS

- Proposed a method for classifying older adults at either low or high falls risk using inertial gait data acquired from a smartphone
- Show how to pre-train a deep neural network to learn feature representation related to human motion using publicly available pedestrian activity data
- Showed how to use a pre-trained deep neural network as feature extractor for falls risk classification
- End-to-end training of a deep neural network for falls risk classification from inertial measurements of gait

Model	ACC (%)	SENS (%)	SPEC (%)
FallsNet (Accel + Gyro)	**86.4**	**85.1**	**87.1**
FallsNet (Accel)	**82.6**	**83.0**	**82.4**
Logistic Regression	58.1	56.6	59.0
Random Forests	63.8	43.9	74.8
SVM	59.6	53.9	62.8

[3] M. Martinez and P. L. De Leon, "Falls Risk Classification of Older Adults Using Deep Neural Networks and Transfer Learning," in review *IEEE J. Biomed. Health Inform.*, Jan. 2019.

FUNDING SOURCES

Sandia National Laboratories, "Summer Faculty Research in Signal Processing and Machine Learning," 2016-2019

Sandia National Laboratories, "Instantaneous Spectral Analysis for Identification and Classification of Bursty Data in Congested Frequency Bands," 2017-2019

Electronic CareGiver, "NMSU 3D Motion Capture System for Biomechanical Data Collection," 2018

Sandia University Part Time

RESEARCH NEEDS

Vector time series classification (in this work we use 6 channels of data)

ML applications seeking high-resolution signal features (time and frequency)

New approaches for unsupervised and semi-supervised ML

Applications needing signal/source separation

New Mexico
Research Spotlight Forum

1/29/2019 Artificial Intelligence & Machine Learning

Real-Time Predictive Guidance and Control for Aerospace Vehicles

Hyeongjun Park, Ph.D.

Mechanical and Aerospace Engineering

New Mexico State University

575-646-2024, hjpark@nmsu.edu

Capability Overview

Sandia National Laboratories | THE UNIVERSITY OF NEW MEXICO | NM STATE UNIVERSITY | NEW MEXICO TECH SCIENCE • ENGINEERING • RESEARCH UNIVERSITY

ABOUT MYSELF – HYEONGJUN PARK

- **Brief biography**
  - Education
    - Ph.D., Aerospace Engineering, University of Michigan 2014
    - B.S./M.S., Aerospace Engineering, Seoul National University, South Korea, 2003/2008
  - Professional Experience
    - Assistant Professor, Mechanical and Aerospace Engineering, New Mexico State University, 2018-present
    - Research Associate, Spacecraft Robotics Lab, Center for Autonomous Vehicle Research, Naval Postgraduate School, 2015-2017
- **Research areas**
  - Onboard real-time trajectory generation
  - Real-time model predictive control
  - Rapid autonomous flight planning with consideration of exclusive-zone constraints
  - Applications: hypersonic vehicles, spacecraft rendezvous and docking, small satellite attitude control

Keywords:

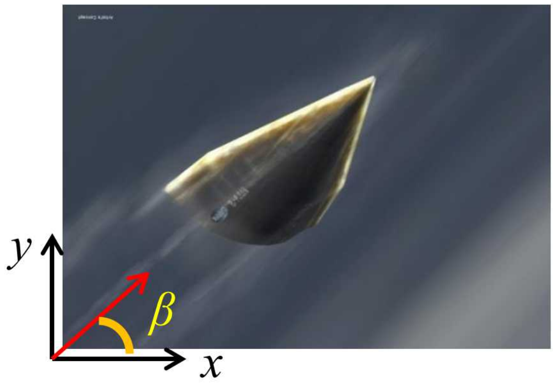
Computational Guidance and Control; Real-Time Optimal Control; Model Predictive Control

CURRENT WORK I – Hypersonic Glider Path Planning

- Time optimal path planning and control based on minimum-time model predictive control
- Two-dimensional model of hypersonic glider

$$\dot{x} = V\cos\beta, \quad \dot{y} = V\sin\beta, \quad \dot{\beta} = \frac{\tan(\alpha_{\max})}{V}u, \quad \dot{V} = a.$$

	Symbol	Description	Constraint
State variables	x	position in x direction	
	y	position in y direction	
	β	heading angle	
	V	velocity	
Control input	u	Normalized bank angle control signal	$-1 \leq u \leq 1$
parameters	a	acceleration	
	α_{max}	maximum bank angle	



DARPA Hypersonic Technology Vehicle (HTV-2)
http://www.darpa.mil/NewsEvents/Releases/2012/04/20.aspx

CURRENT WORK I – Hypersonic Glider Path Planning

- Steering the hypersonic glider from current position to target position in minimum time
- Minimum-time optimal control problem
- Formulation of minimum-time model predictive control

$$\mathbf{0 \le t \le t_f \rightarrow 0 \le \tau \le 1}$$

$$\min_{u(\cdot),\, t_f} \; J_d = t_f + \rho x(N)^T x(N) + t_f \varepsilon \sum_{k=0}^{N-1} \Delta\tau\, u(k)^T u(k),$$

subject to

$$x(k+1) = x(k) + \Delta\tau\, t_f f(x(k), u(k)),$$

$$x(0) = x_0,$$

$$C(x(k), u(k), t_f) \le 0.$$

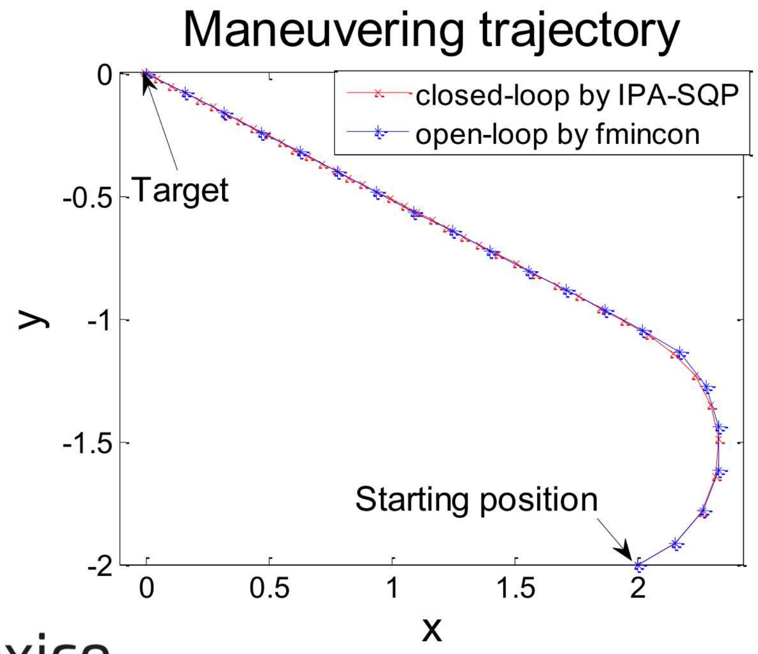
CURRENT WORK I – Hypersonic Glider Path Planning

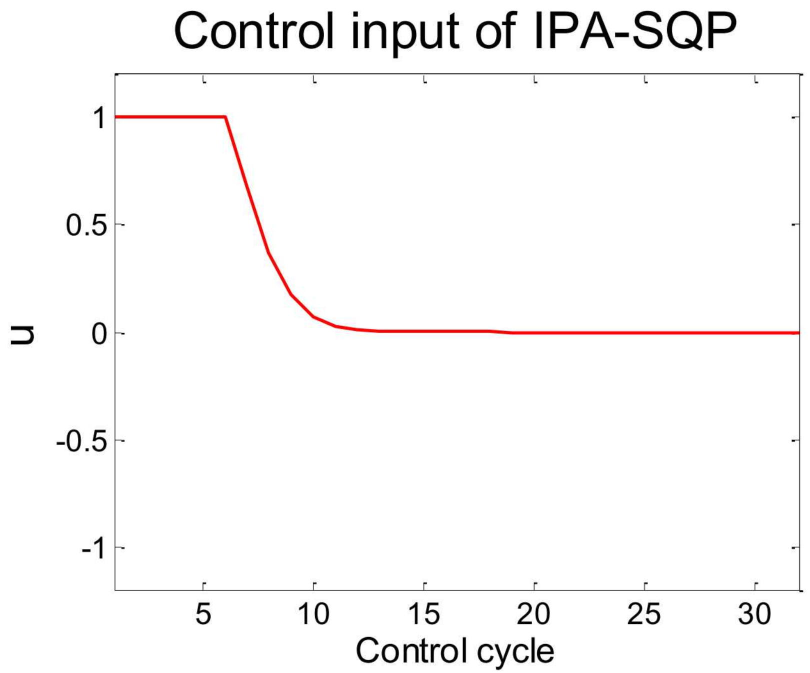
- **Simulation results with a developed solver**
- Glider is initially heading to a different direction from the target position

Closed-loop	fmincon	IPA-SQP
Computation time* (s)	186.16	54.14
Minimum time	11.66	

Reduced 70.92 %

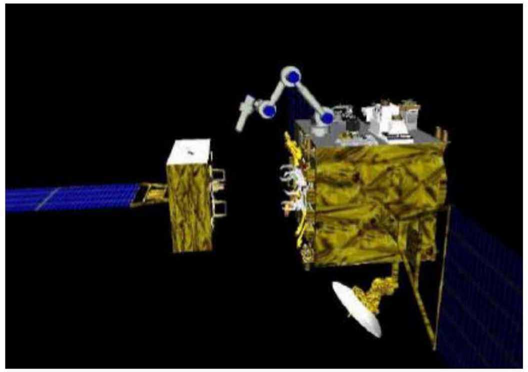
* CPU time usage with Intel® CPU @ 2.10 GHz



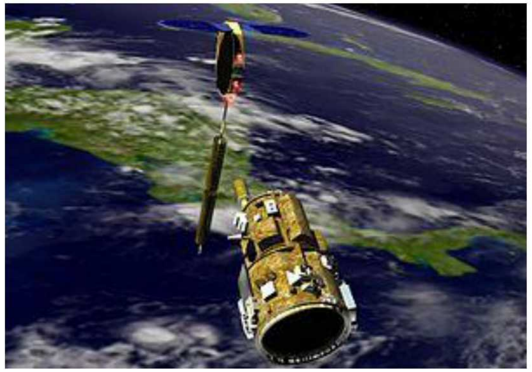


CURRENT WORK II – Spacecraft Onboard Guidance & Control

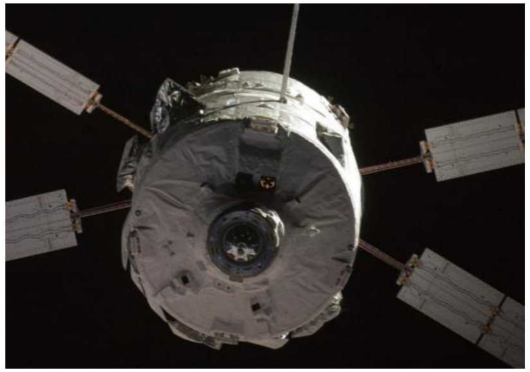
- **Rendezvous and Proximity Operations (RPO)**
  - Docking, berthing, servicing, inspection, active debris removal, etc.



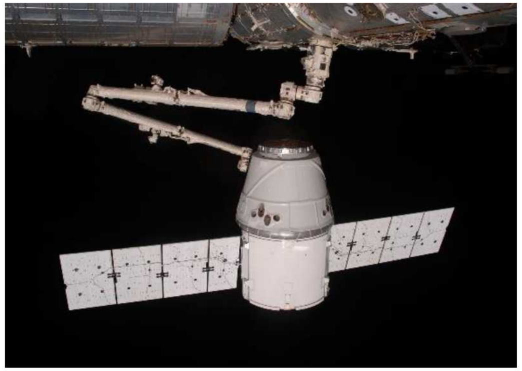
ETS-VII (1998, JAXA)
Image Courtesy of JAXA



DART (2005, NASA)
Image Courtesy of NASA



ATV (2008, ESA)
Image Courtesy of ESA



Dragon (2012, SpaceX)
Image Courtesy of SpaceX

CURRENT WORK II – Spacecraft Onboard Guidance & Control

- **Collision/Obstacle avoidance (keep-out zone avoidance)**
  - Demands to conduct operations in the vicinity of other spacecraft vehicles
  - Increasing number of debris around the Earth

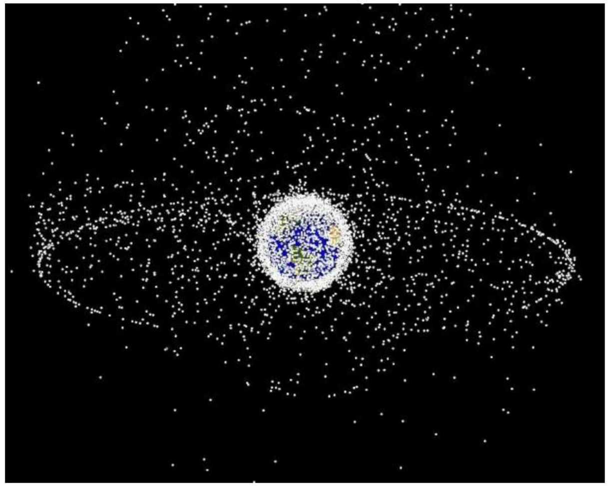


Image Courtesy of NASA

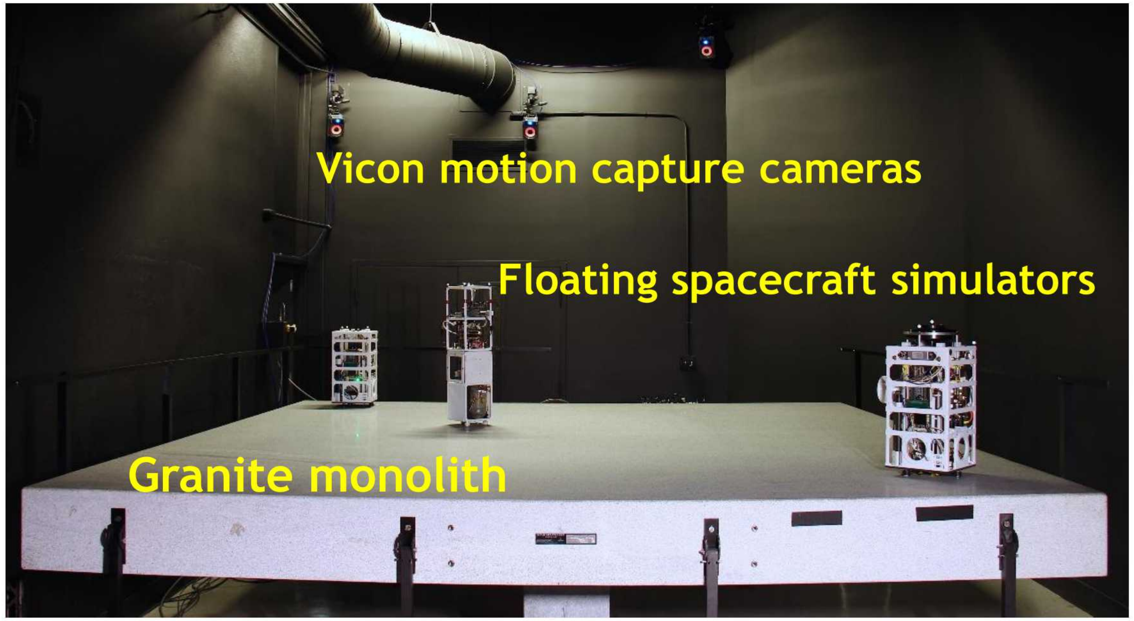
→ Autonomous real-time collision-free RPO while minimizing the propellant consumption

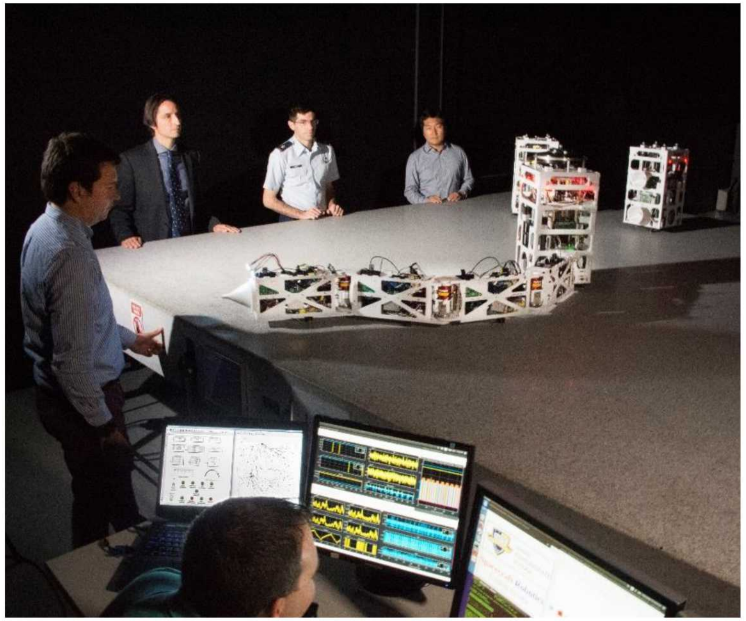
CURRENT WORK II – Spacecraft Onboard Guidance & Control

- **Experimental Testbed**

NPS-POSEIDYN testbed for quasi-frictionless environment

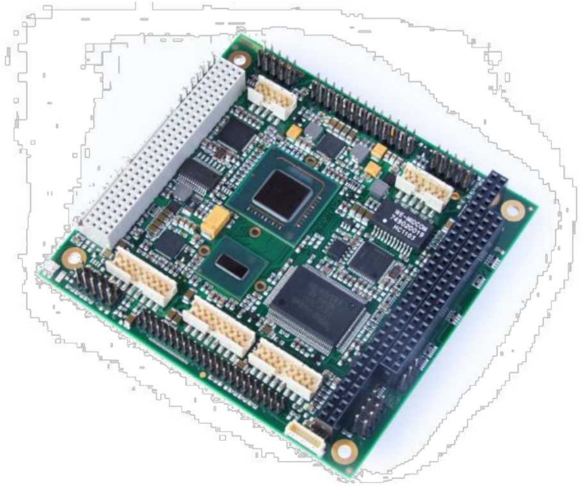
- Naval Postgraduate School – Proximity Operation of Spacecraft: Experimental hardware-In-the-loop DYNamic simulator test bed





CURRENT WORK II – Spacecraft Onboard Guidance & Control

- **Floating Spacecraft Simulators**
  - ~10 kg vehicle
  - 3000 psi 1.8L compressed air tank
  - 3x air bearings (at 60 psi)
  - 8x thrusters (~0.16 N each)
  - Onboard computer
    - PC104-Plus board with Intel Atom 1.6GHz 32-bit with 2GB DDR2 RAM and 8GB SSD
  - Software
    - Ubuntu 14.04 LTS 32 bit edition
    - RTAI kernel patch for real-time execution



CURRENT WORK II – Spacecraft Onboard Guidance & Control

- **Experimental results with keep-out zone constraints**

See Video "Slide158_1"

See Video "Slide158_2"

Linear-Quadratic MPC

Nonlinear MPC

CURRENT WORK II – Spacecraft Onboard Guidance & Control

- **Experimental results – performance comparison**

Experiment	LQ-MPC/DH	NMPC
Control effort [Ns]	4.19	3.68
Time-to-dock [s]	211	202
Avg / Max Comp. time [s]	0.25 / 0.39	0.13 / 0.34

✓ **NMPC achieves shorter docking time and better fuel consumption for this scenario case**

FUNDING SOURCES

- **PI**
  - Predictive guidance and control of NASA Astrobee robots in the International Space Station funded by NASA EPSCoR, New Mexico Space Grant Consortium
    - Collaboration with NASA Ames Research Center

- **Co-PI**
  - Space virtual X-ray telescope sponsored by NASA
    - Formation flying of two small satellites for virtual telescoping
    - Work with NASA Goddard Space Flight Center
  - Satellite alignment system satellite (SAS-SAT) project funded by Northrop Grumman
    - Autonomous alignment and navigation through an optical relative alignment
    - Launch two sets of two CubeSats

RESEARCH NEEDS

- Model and simple mission scenarios for hypersonic vehicles
- Path planning & control requirements as a subset of AI & machine learning
- Onboard real-time trajectory generation requirements

New Mexico Research Spotlight Forum

1/29/2019 Artificial Intelligence & Machine Learning

Knowledge discovery and data mining from time series and graph data

Huiping Cao

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Capability Overview

Sandia National Laboratories | THE UNIVERSITY OF NEW MEXICO | NM STATE UNIVERSITY | NEW MEXICO TECH SCIENCE • ENGINEERING • RESEARCH UNIVERSITY

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ABOUT YOURSELF

- Huping Cao, Associate Professor in Computer Science at New Mexico State University.
- Research areas
  - Data mining: time series mining, graph mining
  - Machine learning: probabilistic models, Convolutional Neural Networks
  - Databases: graph search
- Research group interests, size and demographics
  - Basic & applied data sciences
  - 4 PhD students, 2 UGs
  - 2 Hispanics, 1 Caucasian, 4 Chinese

Keywords:

Time series, graphs, social networks, smart grids, Bayesian networks, deep learning, graph search

CURRENT WORK IN ARTIFICIAL INTELLIGENCE/ MACHINE LEARNING

1. Big data-driven Context-Sensitive Impact Discovery (CSID) in complex systems.
   - Example 1: identify influence relationships of people in social networks
   - Example 2: discover how specific types of events cause other types of events in high-performance computing (HPC) systems
2. Smart grid monitoring
   - Example: classify different types of disturbances from PMU data
3. Feature selection from multi-variate time series (MTS) data
   - Example: in human body movement tracking, detect which sensors are more important for different types of activities
4. Identify new knowledge from articles
   - Example: given two similar articles, how do we know that one article has new knowledge and how we can identify new knowledge.

FUNDING SOURCES

1. RII Track-1: The New Mexico SMART Grid Center: Sustainable, Modular, Adaptive, Resilient, and Transactive. (PI: William Michener). NSF OIA-1757207, $3,933,361 (for year 1), 09/15/2018 - 08/31/2023. Senior Personnel.
2. Preparing Highly Qualified Students with Financial Need for Careers in Computing and Cyber-Security through Evidence-Based Educational Practices. NSF DUE-1833630, $3,969,365, 10/01/2018 - 09/30/2023, PI. Co-PI: Enrico Pontelli.
3. BIGDATA: Collaborative Research: F: Discovering Context-Sensitive Impact in Complex Systems. NSF IIS-1633330, $361,791, 09/01/2016 - 08/31/2019, NMSU PI.
4. iCREDITS: interdisciplinary Center of Research Excellence in Design of Intelligent Technologies for Smartgrids. (PI: Enrico Pontelli). NSF HRD-1345232. $4,999,721. Co-PI.

RESEARCH NEEDS

1. What are the applications apply data mining & machine learning techniques in the areas of Cybersecurity and unmanned systems
2. What are the datasets that we can use to discover new knowledge in the areas of Cybersecurity and unmanned systems

New Mexico Research Spotlight Forum

1/29/2019 Artificial Intelligence & Machine Learning

Hybrid supervised-unsupervised algorithms

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Capability Overview

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ABOUT YOURSELF

- Assistant Prof of CS at NMT
- CS Theory, Artificial Intelligence, ML
- Collaborative research mainly between universities (UC Davis, UCSD, IU)

Keywords:

Hybrid Algorithms, Biological Spiking Networks

CURRENT WORK IN ARTIFICIAL INTELLIGENCE/ MACHINE LEARNING

- Big Themes
  - Advancing Science
  - Biologically inspired networks
- Techniques/methodology of focus
  - Hybrid Algorithms (combining Supervised and Unsupervised algorithms)
  - Sleep
- Projects
  - Nutrition and Health
  - Weather prediction
  - Orthopedic Surgery
  - Cybersecurity
  - Criminology
  - Putting networks to sleep

CURRENT WORK IN ARTIFICIAL INTELLIGENCE/ MACHINE LEARNING

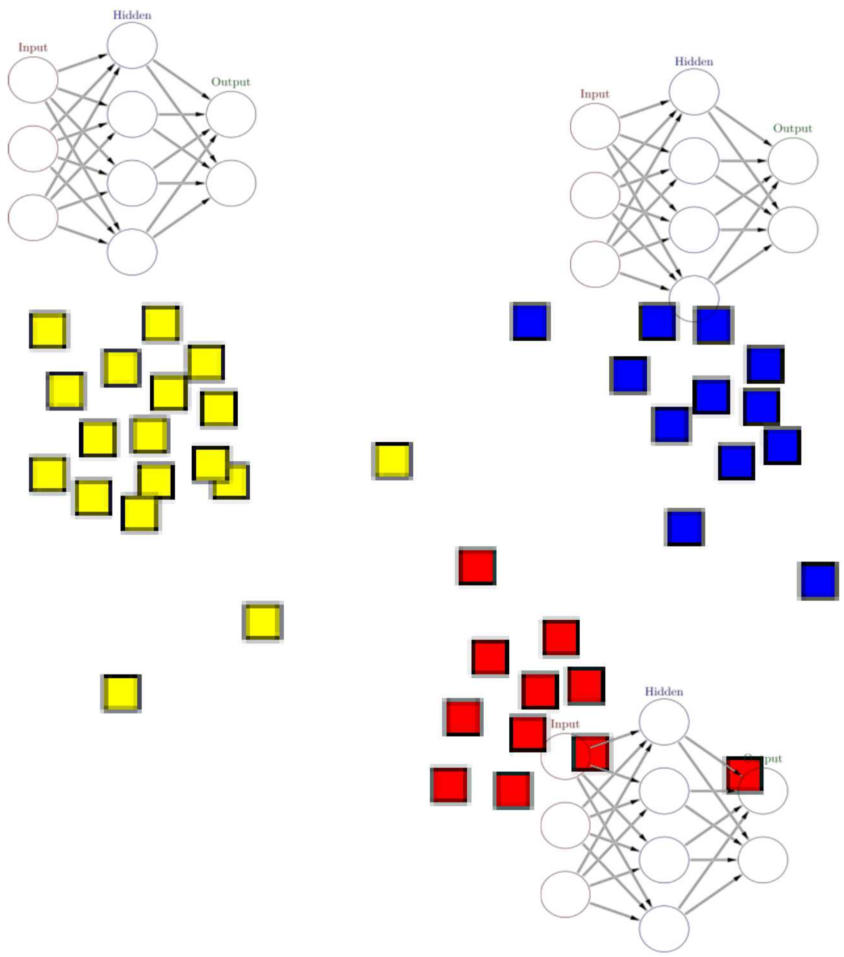
- Hybrid Algorithms

Use clustering algorithms to partition data

With each partition, develop an ML m

New data

- Cluster with closest centroid
- Majority of nearest clusters
- Weighted average of nearest clusters



CURRENT WORK IN ARTIFICIAL INTELLIGENCE/ MACHINE LEARNING

- N/w of infected devices controlled together
- User unaware of infection
- Network traffic pattern has been successfully used in detection

Data:

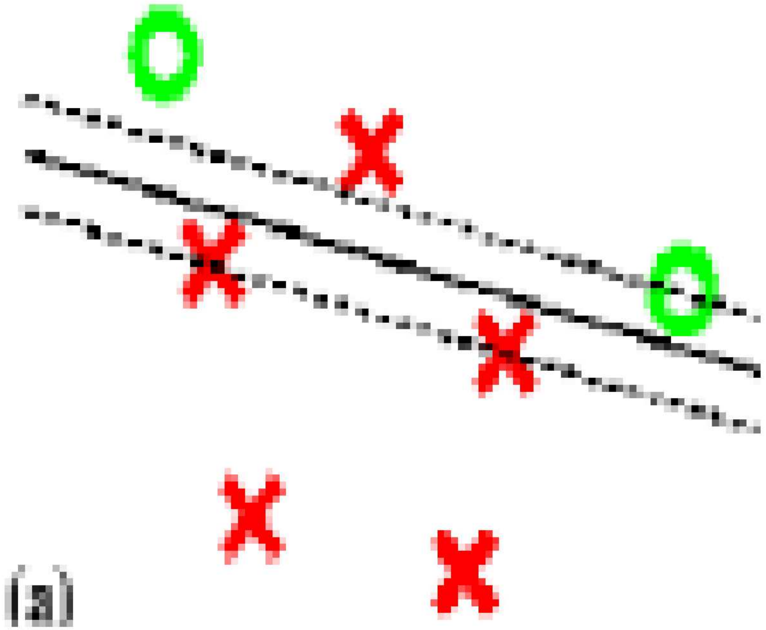
- The CTU-13 dataset captured by CTU, Czech Republic [Garcia et al. 2014].
- a reduced dataset of 199,960 rows from botnet traffic from the Neris bot.

CURRENT WORK IN ARTIFICIAL INTELLIGENCE/ MACHINE LEARNING

Exploratory research Direction

- ML models
- Techniques for skewed class
- Anomaly detection

Motivation behind clustering



CURRENT WORK IN ARTIFICIAL INTELLIGENCE/ MACHINE LEARNING

Methodology and Results

- Features: flow duration, protocol, source port, direction, and status.
- Clustering and then training
- Machine learning results

Model	ACU	CA	F1	Precision	Recall
Random Forest	0.943	0.991	0.989	0.99	0.991
Naïve Bayes	0.934	0.975	0.97	0.969	0.975
kNN	0.86	0.988	0.984	0.982	0.988
Neural Network	0.923	0.985	0.98	0.977	0.985
Logistic Regression	0.879	0.975	0.962	0.95	0.975
SVM	0.561	0.099	0.144	0.948	0.099

Future Works

- Compare with cluster based anomaly detection
- Understand clusters

CURRENT WORK IN ARTIFICIAL INTELLIGENCE/ MACHINE LEARNING

Biologically inspired

Sleep

- Generalization
- Abstraction
- Memory consolidation

CURRENT WORK IN ARTIFICIAL INTELLIGENCE/ MACHINE LEARNING

Artificial Neurons and networks
- Thresholds weighted inputs
- Positive and negative inputs
- Clocked
- Feed forward, produces a result
- Perceptron learning rule (error based)

Biological Neurons and networks
- Probabilistically thresholds weighted input (may fire with no input)
- Excitatory and inhibitory neurons
- Sums inputs over time
- Highly recurrent, produces sustained activity
- STDP or Hebbian Rule

CURRENT WORK IN ARTIFICIAL INTELLIGENCE/ MACHINE LEARNING

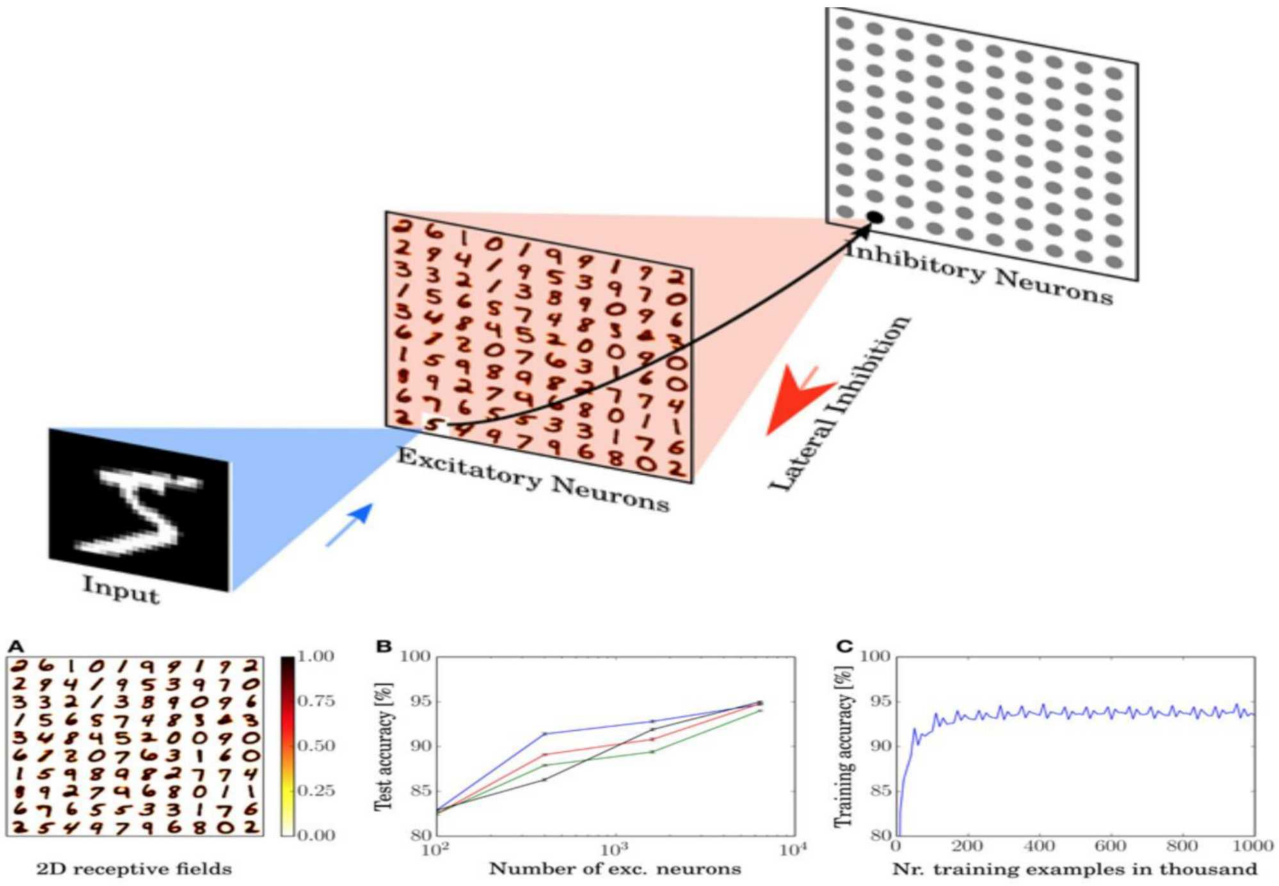
Input: 2D spiking network

Intermediate layer: input layer is randomly connected

Inhibitory layer to stabilize the intermediate layer

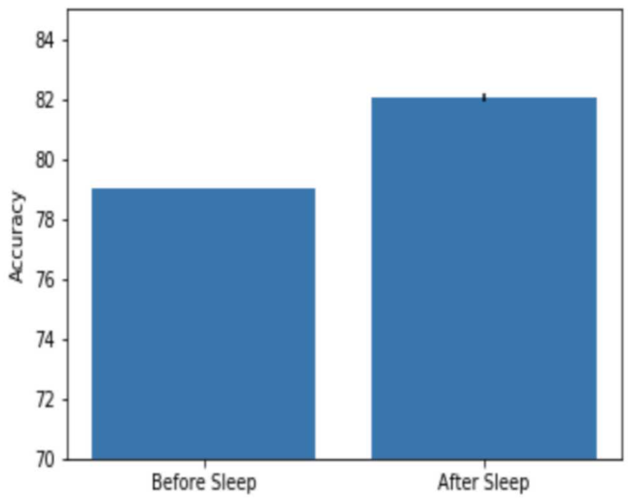
Learning: STDP

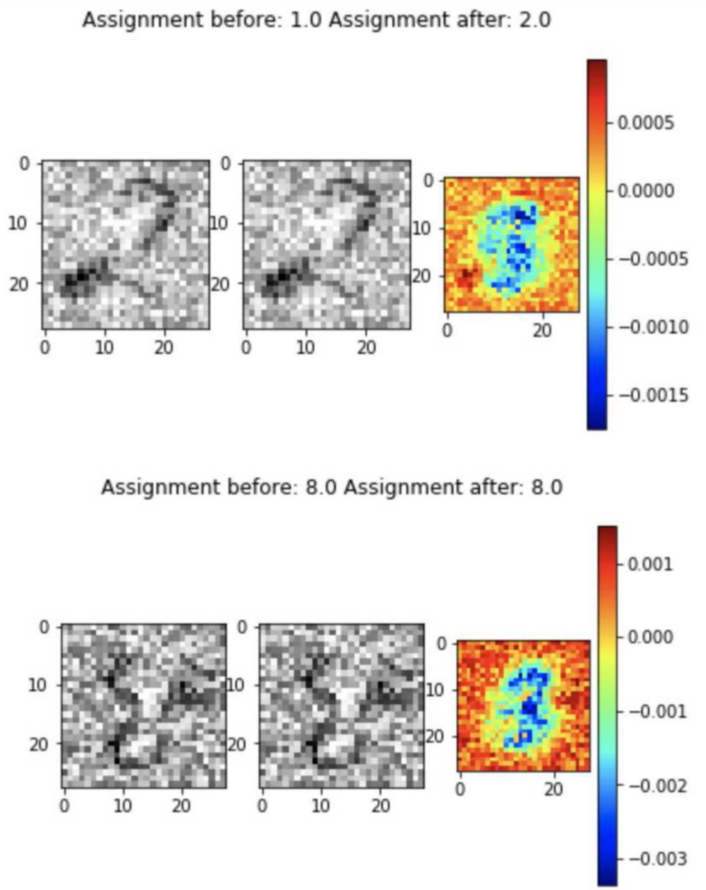
CURRENT WORK IN ARTIFICIAL INTELLIGENCE/ MACHINE LEARNING



CURRENT WORK IN ARTIFICIAL INTELLIGENCE/ MACHINE LEARNING

1. Train spiking network on MNIST
   1. → Evaluate spiking network on MNIST
2. Train spiking network on MNIST
   1. → Sleep period (Increased leak and AMPA currents) with averaged input
   2. → Evaluate spiking network on MNIST





FUNDING SOURCES

Funded by:

NSF (REU)

NSF Subcontract from IU

Consulting at UCSD

RESEARCH NEEDS

Past works include

- Exploratory work on cyber security – but from an academic standpoint
- Using AI methods to validate criminology

Looking for collaborators with

Specific questions in understanding attacks

FUTURE FORUMS

3/5/19	Engineering Mechanics and Dynamics
4/23/19	Social Sciences and Decision Making
6/4/19	Resilient Infrastructure (SMART Grid)
7/16/19	Advanced Manufacturing and Robotics
8/27/19	Biomedical Engineering and Informatics

**dates and topics may change*